ALASKA LEGISLATURE COMMITTEE FILES, 2003-2004 8672

11217 SENATE LABOR & COMMERCE

Many policyholders are paying lower premiums because their insurers consider credit information. Respondents to our survey said that more than half of their policyholders are in this category. Their estimated percentages of policyholders paying lower premiums as a result of their good credit histories range from 50% to 90% of total auto or homeowners policyholders. If credit information could no longer be used, then this majority of policyholders – in some cases, an overwhelming majority – would have to pay higher premiums.

The insurers responding to our survey are only a sampling of companies. We are confident that there are other NAII members and certainly other insurers outside of the NAII membership that have found credit information as a way to make insurance coverage more available at lower premiums to more consumers. Clearly, policyholders have benefited from companies' use of credit information, whether it be obtaining insurance, keeping insurance, or paying lower premiums for insurance.

There have been many anecdotes and several theories offered about how the use of credit information may affect insurance markets. Insurance companies are not involved in anecdotes or theories. They are real businesses that are providing protection to millions of drivers and homeowners across the nation, in part at least, because the insurers have credit information as an available tool for underwriting and rating.

Too often the debate over insurers' use of credit information has focused on the notion that insurance companies use insurance scores to reject people. But insurance companies are not in the business of not writing business. Insurance companies are in the business of writing policies covering cars and homes. Credit information gives insurers a tool to underwrite and fairly price personal lines coverages.

In insurance markets today, drivers with less than perfect driving records and homeowners whose houses may fall short of so-called "traditional" underwriting factors are being accepted and renewed by insurance companies because they have good credit histories.

Most people have good credit histories. The use of insurance scores by personal lines insurance companies gives people with favorable insurance scores a better chance to find insurance, and often find it at prices that save them money. On the other hand, restricting the use of credit information presents a real danger that consumers who are able to find fairly priced insurance protection today will not be able to find that insurance tomorrow.

Concerns about Insurers' Use of Credit Information

Some concerns have been raised about insurers' use of insurance scores. These concerns include the following:

1. There is no proven correlation between credit-based insurance scores and the risk of loss.

2. There is no proof that a person's credit history causes insured losses.

3. Insurance scores discriminate against some consumers, especially low-income consumers and minorities.

4. Insurance scores simply overlap with variables already taken into account in an insurer's underwriting and/or rating process.

5. Insurance scores are based on inaccurate credit data.

Correlation

The Casualty Actuarial Society awarded its 2000 Ratemaking Prize to James E. Monaghan for his paper, "The Impact of Personal Credit History on Loss Performance in Personal Lines." Mr. Monaghan compiled a database of 170,000 automobile insurance policies. He then examined the credit history of the named insured in each of the policies in order to determine whether the insured's credit characteristics correlated with the insured's loss ratio relativity. Monaghan's paper details how variations in each of the following credit characteristics correlates to variations in loss ratio relativity:

- amounts past due at least thirty days
- bankruptcies, tax liens, civil judgments and foreclosures
- collection records transferred to a collection agency
- status of trade lines (trade lines include credit cards, installment loans, student loans, etc.)
- age of oldest trade line
- non-promotional credit inquiries
- leverage ratio on revolving-type accounts
- revolving account limits

Monaghan's conclusion is that each of these credit characteristics showed a "systematic predictive power" on loss ratio relativities.

Mr. Monaghan performed a similar analysis on a homeowners insurance database containing $120 million in earned premiums. His paper states the following conclusion:

> "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. **** The similarities between the loss ratio relativities for [the homeowners and auto] 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."[13]

Mr. Monaghan's finding of a correlation between particular credit characteristics and loss ratios is the concept on which insurance scores are based. An insurance score combines the predictive power of a number of particular credit characteristics to produce an evaluation of risk of loss that is more accurate and fairer than the predictive power of any one credit characteristic.

In 1996, at the request of the National Association of Insurance Commissioners (NAIC), Fair, Isaac retained Tillinghast-Towers Perrin to perform a regression analysis of Fair, Isaac's insurance bureau scores and loss ratio relativities. The analysis considered data from nine companies (three auto carriers, five homeowners carriers and one personal property insurer). Tillinghast-Towers Perrin concluded:

> "From the data and P-Values, we conclude that the indication of a relationship between Insurance Bureau Scores and loss ratio relativities is highly statistically significant. In a more technical sense, the conclusion is that it is very unlikely that Insurance Bureau Scores and loss ratio relativities are not correlated based on this data.
>
> The data for all companies included in this study except Company 2 indicates at least a 99% probability that a relationship exists. The data for Company 2 indicate a 92% probability that there is a relationship. A layman's interpretation of this result could be that it is very likely there is a correlation between Insurance Bureau Scores and loss ratio relativities."[14]

In December 1999, the Virginia Bureau of Insurance issued a report to the Virginia General Assembly on insurers' use of credit information. The Bureau examined the development and application of Fair, Isaac's scoring system and reached the following conclusion:

> "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."[15]

On November 15, 2002, the Risk Classification Subcommittee of the American Academy of Actuaries submitted a report to the NAIC.[16] The report points out the strengths and weaknesses of the Monaghan paper, the Tillinghast analysis and the Virginia Bureau of Insurance's report. The introductory section to the subcommittee's report states:

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[13] James E. Monaghan, "The Impact of Personal Credit History on Loss Performance in Personal Lines," *Casualty Actuarial Society Forum*, Winter 2000, p. 96.
[14] *Insurance Bureau Scores vs. Loss Ratio Relativities* (Tillinghast-Towers Perrin, 1996), pp. 4-5.
[15] *Use of Credit Reports in Underwriting* (Virginia Bureau of Insurance, 1999), p. 19.
[16] *The Use of Credit History for Personal Lines of Insurance; Report to the National Association of Insurance Commissioners* (American Academy of Actuaries, Risk Classification Subcommittee, November 15, 2002)

"The subcommittee was not asked to evaluate the effectiveness of credit history as a tool in the underwriting and rating of personal lines of insurance, and therefore such an evaluation is not an element of this report. However, the subcommittee believes that credit history can be used effectively to differentiate between groups of policyholders and therefore it is an effective tool. This recognition is based on review of the four papers listed above, especially the Monaghan paper, and on the subcommittee's members' personal knowledge as obtained through the development and/or review of rating models based on credit history."[17]

In March 2003, the University of Texas McCombs School of Business Bureau of Business Research issued a study of the relationship between credit history and insurance losses.[18] The study confirmed the strong relationship between credit-based insurance scores and the likelihood of insured losses. The study concludes:

"Using logistic and multiple regression analyses, the research team tested whether the credit score for the named insured on a policy was significantly related to incurred losses for that policy. It was determined that there was a significant relationship. In general, lower credit scores were associated with larger incurred losses.

* * * *

A regression analysis of the relative loss ratio on credit score was highly significant (p<.0001). This indicates that there is less than a 1 in 10,000 chance that the relationship observed between credit score and relative loss ratio could be due to chance alone.

* * * *

Over the entire data set, the average loss per policy was $695, but for those policies in the lowest 10 percent of credit scores, this average loss was $918, whereas within the highest credit score decile, the average loss per policy was $558. Thus, the average loss per policy is higher for the lowest credit score deciles and lower for the higher credit score deciles."[19]

The Monaghan paper, the Tillinghast analysis, the Virginia Bureau of Insurance report, the statement of the American Academy of Actuaries Subcommittee and the University of Texas study confirm the correlation between credit information and loss ratios. But perhaps the most convincing evidence of the correlation is the real world experience of insurance companies. Personal lines insurers used credit information in the past, and they are continuing to use credit information to underwrite and rate. Insurance companies are rational, economic entities. It would make no sense for companies to base their underwriting and rating decisions and their economic futures on information which fails to predict the likelihood of loss. The owners of an insurance company would not stand for the company's continued use of information which does not correlate to loss ratios.

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[17] Ibid, p.3

[18] *A Statistical Analysis of the Relationship Between Credit History and Insurance Losses* (University of Texas at Austin, McCombs School of Business Bureau of Business Research, March 2003)

[19] Ibid, Executive Summary and pp. 9 and 10.

Causation

Some have argued that insurers' use of credit information should be prohibited because no cause-and-effect relationship can be established between credit history and insured loss. This demand for proof of causation is curious. Causality is not a precondition for any other risk classification. For example, driving record is a well-established risk classification for automobile insurance, but insurers are not required to prove that past driving accidents *cause* future accidents. Many states allow auto insurers to use marital status and good student status as risk classifications, but there is no expectation that marital status or poor grades *cause* accidents.

In his paper, James Monaghan mentions Section 5.2 of Actuarial Standards of Practice #12 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." *(emphasis added)*

Therefore, according to established actuarial principles, causality cannot be made a requirement for a risk classification, but any risk characteristic "should be neither obscure nor irrelevant" to the likelihood of loss. There must be some reason why a characteristic relates to the likelihood of loss.

The link between credit history and loss potential has been studied by scholars independent of the insurance industry, in fields such as psychology, safety engineering, occupational medicine, consumer research, and risk perception.[20] The studies offer two common sense theories on why

[20] J.G. Baradell & K. Klein, "Relationship of Life Stress and Body Consciousness to Hypervigilant Decision Making," *Journal of Personality and Social Psychology*, 64 (1993), 267-273.

credit history relates to loss potential. First, stress related to credit problems may lead to negligent behavior which could evidence itself in driving and home maintenance. Second, financial irresponsibility may indicate a risk-taking personality. A person who is willing to take on the risks of high credit card debts is likely to be the same type of person who is willing to try to beat a red light or leave a needed repair go until next year.

Insurers use credit information because of its predictive power, not because of the reasons that explain its predictive power. One can agree or disagree with the reasons why credit information works, but the fact of its predictive value is clear. Nevertheless, it is significant that support for the link between credit information and loss potential exists in the academic lite ature and is intuitively satisfying.

Unfair Discrimination

The charge that insurance scores discriminate against low-income consumers and minorities is easy to make, but it is a charge that is not backed up by any facts.

The fact is that insurance scores only consider a person's credit experience. Insurance scores do not consider any of the following information:

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

The 1997 NAIC white paper on the use of credit information considered charges that insurers' use of credit histories has a disproportionate impact on protected classes. The paper could find no studies supporting the charge. The white paper states:

> "Some regulators and consumer representatives have expressed their belief that the use of credit history should be prohibited as a matter of public policy. Some have also expressed concern that the use of credit history for underwriting or rating

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B. Brehmer, "Psychological Aspects of Traffic Safety," *European Journal of Operational Research*, 75 (1994), 540-552.

L. Evans & P. Wasielewski, "Do Accident Involved Drivers Exhibit Riskier Everyday Driving Behavior?" *Accident Analysis and Prevention*, 14 (Feb. 1982), 57-64.

E. Knowles & H. Cutter, "Risk Taking as A Personality Trait," *Social Behavior and Personality*, 1 (1973), 123-136.

S Livingstone & P. Lunt, "Predicting Personal Debt and Debt Repayment," *Journal of Economic Psychology*, 13 (March 1992), 111-134.

P. Lunt & S. Livingstone, "Everyday Explanations for Personal Debt," *British Journal of Social Psychology*, 30 (Dec. 1991), 309-323.

S. Streufert, S.C. Streufert & A. Denson, "Information Load Stress, Risk Taking and Physiological Responsively In A Visual-Motor Task," *Journal of Applied Social Psychology*, 13 (1983), 145-163.

C. Walker, "Financial Management, Coping and Debt In Households Under Financial Strain," *Journal of Economic Psychology*, 17 (Dec. 1996), 789-807.

may be a surrogate for prohibited factors, such as race, or for factors already considered, such as age. However, regulators know of no studies in the insurance field that demonstrate that the use of credit history in underwriting an insurance risk has had a disproportionate impact on protected classes although they have been advised that there have been studies of other industries which suggest such an impact."[21] *(emphasis added)*

The Virginia Bureau of Insurance's report, mentioned above, analyzed whether the Fair, Isaac insurance scores result in discrimination based on income or race. The Bureau could find no support for charges of unfair discrimination. The Bureau's report states:

> "Thus, average credit scores, medium household incomes, and ratio 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."[22]

During the NAIC's Market Conduct and Consumer Affairs (EX3) Subcommittee's December 6, 1998 hearing on credit reports, Progressive Insurance Company presented information on its experience in using credit information. Progressive reviewed insurance scores across different areas of population density. The data offered to the Subcommittee showed that insurance scores in densely populated areas were about the same as scores in sparsely populated areas. Thus, consumers living in urban areas have about the same distribution of insurance scores as consumers living in suburban and rural areas.

The Washington State Insurance Commissioner and the Alaska Division of Insurance have issued reports on the impact of insurance scores on various groups of consumers. Both reports include indications that insurance scores may impact demographic groups differently. However, both reports cautioned that it would be premature to draw any firm conclusions from the reports' research. The Washington report states:

> "Therefore, an overall conclusion that credit scoring generally does or does not have a particular consistent, quantifiable, unequal negative effect on certain demographic groups is premature. Possible negative effects will have to be directly evaluated using data on the outcomes for each insurer's practices and clientele, at least until there is more understanding of when and why particular unequal impacts result."[23]

The Alaska report states:

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[21] *Credit Reports and Insurance Underwriting* (National Association of Insurance Commissioners, 1997), p. 14.
[22] Virginia Bureau of Insurance, p. 16.
[23] *Effect of Credit Scoring on Auto Insurance Underwriting and Pricing* (Washington State University, Social & Economics Sciences Research Center, January 2003), p. 17.

"Based on the limited data received and evaluated so far, insurance credit scoring in Alaska appears to have different effects on different groups of Alaskan insurance consumers. In the aggregate, consumers that reside in higher income/high percentage Caucasian zip codes may be less impacted by the use of the consumer's credit history. It is premature to determine whether the policyholder distribution between preferred, standard and nonstandard markets is due primarily to credit history or to other underwriting and rating factors. However, the limited data does suggest that unequal effects exist on consumers with varying income and ethnic characteristics."[24]

The question of whether insurers' use of credit information unfairly discriminates against low-income consumers and minorities continues to be studied. The American Academy of Actuaries' November 15, 2002 report to the NAIC concluded that none of the four papers it reviewed "contained the necessary information for us to evaluate whether credit-related insurance scoring results in a disproportionate impact for protected classes or for low-income policyholders."[25] The report went on to provide some general guidance to the NAIC on designing a study of the impact of credit-based insurance scores. An NAIC working group is now attempting to develop a proposal for how the NAIC could undertake a study of the impact of insurers' use of credit information on various groups of consumers.

Overlapping Variables

Critics of insurers' use of credit information have argued that insurance scores simply duplicate other variables already being used by insurers and thus insurance scores have no independent predictive value. It is argued that the overlap of insurance scores with other variables results in unfairness to consumers.

In its 2001 study on insurance scoring, Conning & Company used the data in James Monaghan's Casualty Actuarial Society paper to analyze the relationship between insurance scores and other automobile insurance rating variables. Conning found that insurance scores did not overlap with other variables. The study states:

> "Conning concludes that, based on its careful review of the CAS study, the application of credit data to personal automobile insurance underwriting enables much better loss ratio predictions. When credit data were appended to traditional rating variables (i.e., driver age), there were significant differences in loss ratio performance – suggesting that credit data are not likely to overlap other rating variables significantly. Insurers conducting their own analysis of credit characteristics and loss ratio performance must examine their data carefully to determine if multicollinearity or spurious correlation is present."[26] *(emphasis added)*

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[24] *Insurance Credit Scoring in Alaska* (Alaska Division of Insurance, February 21, 2003), p. 15.
[25] American Academy of Actuaries, p.30
[26] *Insurance Scoring in Personal Automobile Insurance* (Conning & Company, 2001, pp. 70-71.

The University of Texas study also analyzed whether credit-based insurance scores have a predictive power that is independent from other variables. The study concluded that insurance scores were independent predictors of loss. The Texas study states:

> "[L]ogistic and multiple regression analyses examined whether the revealed relationship between credit score and incurred losses was explainable by existing underwriting variables, or whether the credit score added new information about losses not contained in the existing underwriting variables. It was determined that credit score did yield new information not contained in the existing underwriting variables.
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> * * * *
>
> Additionally, incorporating underwriting variables used by the companies through the use of relative loss ratios, it was found that there was still a statistically significant relationship between credit scores and the relative loss ratio for policies (Charts 4, 5), <u>so standard underwriting variables do not explain the observed statistically significant relationship between credit scores and losses</u>. (The correlation between credit score and relative loss ratio is .95, which is extremely high and statistically significant.) The lower a named insured's credit score, the higher the probability that the insured will incur losses on an automobile insurance policy, and the higher the expected loss on the policy."[27] (*emphasis added*)

Accuracy of Credit Data

Thousands of businesses which have nothing to do with insurance use credit information every day. There are a few cries that these businesses should be prohibited from using credit data because the data is inaccurate. However, critics of insurance scores charge that insurers, whose use of credit information is much more limited than many other businesses, should be barred from using credit data because the data is erroneous.

The accuracy of credit data stands up to scrutiny. Certainly credit data is at least as accurate as MVRs and claims reports which were discussed above. The 1996 amendments to the FCRA imposed additional requirements on consumer reporting agencies and credit reporters to assure the accuracy of credit information.[28] The amendments also created strict time frames for investigating and correcting information which is disputed by consumers.[29]

Research shows that the error rate in credit reports is low. Trans Union reviewed the experiences of 400,000 consumers whose insurance coverage was affected by the use of credit information. The company discovered that only 0.2% of the insurance consumers disputed the information in their credit reports. Furthermore, only 0.07% of these consumers required corrections to their credit reports.

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[27] University of Texas, Executive Summary and p. 13.
[28] 15 U.S.C. §1681s-2(a).
[29] 15 U.S.C. §1681i.

Conclusion

During the deliberations on the NAIC white paper, several regulators cautioned against restricting insurers' use of credit information. The white paper observes:

> "Other regulators believe that if an insurer is deciding whether it will write in a certain geographic area, removing an underwriting tool may create a disincentive for it to enter the market. Insurers will enter a market only when they are comfortable they can underwrite, make a profit, and exit the market if the results are poor. <u>Underwriting restrictions are not conducive to expanding the market.</u> These regulators believe that the premise that credit reports are used not to write in certain areas may be flawed. <u>They believe that regulators should consider the potential harm that may be caused to the market they are trying to assist, before imposing restriction.</u>"[30] *(emphasis added)*

The wisdom of these regulators should be heeded. The use of insurance scores for underwriting and rating has helped to make insurance coverage more available for millions of drivers and homeowners. Restrictions on the use of insurance scores should be approached with great caution.

[30] National Association of Insurance Commissioners, p.4.

PROGRESSIVE

Statement of Progressive Insurance to the Alaska House State Affairs Committee in Opposition of Senate Bill SB 13

April 8, 2003

Progressive Insurance is the largest writer of private passenger auto insurance through independent agents and the third largest auto insurer in the country. We do business in 48 states and we are represented by more than 30,000 independent agencies throughout the country.

In Alaska Progressive is the fifth largest writer of auto insurance. We sell insurance through over 60 independent agents in Alaska, as well as through our call center and the Internet. We currently have over 17,000 policyholders in Alaska; over 13,000 of these policies were sold through our local independent agents.

In this statement, I would like to address the following issues:

- Why we use credit scoring in insurance
- How Progressive uses credit scoring
- Answer concerns in relation to insurance credit scoring and the Alaska Division of Insurance Credit Study
- Explain why Progressive is opposed to HB 5 and HB 47

Why we use credit scoring in insurance

It has been proven both by Progressive's actual loss experience and by independent actuarial analysis that credit is a powerful and independent predictor of future losses. It is just one of many factors Progressive considers in determining rates; we also use other information, like driving record, gender, age, marital status, vehicle model/make/year, and garaging address.

In Alaska, Progressive filed detailed actuarial data in support of our use of credit. This data was reviewed and approved by the Alaska Division of Insurance as part of the rate filing process.

Using credit allows insurers to more accurately predict future losses and to set premiums that will adequately cover these losses. Using credit as an underwriting factor has allowed Progressive - and our agents - to offer more accurate and <u>lower rates</u> to more people. Since Progressive began using credit, we have been able to offer standard and preferred rate levels to many consumers who otherwise would have been eligible only for nonstandard rates. We estimate that about two thirds of our policyholders have qualified for lower rates due to the use of credit information.

There are many studies that demonstrate the predictive power of credit in insurance such as the 2000 paper by James E. Monaghan "The Impact of Personal Credit History on

Loss Performance in Personal Lines", the 1999 report by the Virginia Bureau of Insurance to the Virginia General assembly, the November 2002 report by the Risk Classification Subcommittee of the American Academy of Actuaries to the National Association of Insurance Commissioners.

The most recent such study was just released on March 6, 2003 by the University of Texas. The study entitled "A Statistical Analysis of the Relationship Between Credit History and Insurance Losses" matched policyholder loss records for more than 153,000 auto insurance policies supplied by the five leading auto insurers. It demonstrated a strong correlation between credit scores and the risk of loss, confirming that credit scoring is a useful tool for predicting future loss experience.

How Progressive uses credit scoring

Progressive has been using credit information in our Alaska program for over six years. We have consistently been on the forefront of providing transparency to our credit scoring methodology and in improving our credit scoring practices to ensure that our customers receive fair and equitable rates.

We have devoted significant effort and resources to our credit practices, and we have shown a great deal of commitment to the responsible use of credit in insurance. We were actively involved in the discussions around credit in the last Alaska legislature and since then we have taken a number of measures to address the issues that were brought up last year:

1. We have filed our current credit scoring methodology and detailed actuarial support with the Alaska Division of Insurance. Our model is public information; there is no "black box".
2. Progressive does not use credit information to refuse to insure a consumer, non-renew, or cancel an existing customer.
3. Credit information that is disputed by the consumer with the credit-reporting agency is not considered in our insurance scoring algorithm.
4. All identified medical and business/commercial debt and liens are excluded from all Progressive credit scoring methods.
5. An applicant or insured who experiences an adverse action as a result of the use of credit information is advised how he or she can obtain a free copy of their credit report.
6. We provide a list of the reasons for an adverse action due to the use of credit to consumers upon request.
7. Progressive is committed to sharing information about how we use credit with regulators, the media, and consumers. We want consumers to understand how credit affects their insurance premiums and we want to help them in developing a plan to improve their credit scores.
8. We have pioneered the use of a new Credit Assistance team for our customers and agents in Michigan and Texas, and we are in the process of rolling that out to more states. The Credit Assistance team can be reached through a toll-free number and it provides:

    a. Personalized reports to applicants describing how their score on each of the variables considered in the credit-scoring algorithm compares to the average.

b. Reasonable credit exceptions based upon prior credit history for persons whose credit information is unduly influenced by extraordinary life events (i.e., catastrophic injury, death of a spouse, business loss etc.).

Concerns around the use of insurance credit scoring

The use of credit information in insurance has received a lot of scrutiny by legislators, regulators, consumers and the media. Concerns have been raised as to whether insurance scoring might result in unfair discrimination.

Credit scores focus mainly on a person's bill-paying behavior and use of available credit. If a consumer has been responsible in his or her use of credit, it will reflect positively on the score. Credit reports do not contain any information on income, race, ethnicity, creed, nationality, gender, marital status, physical handicap or disability.

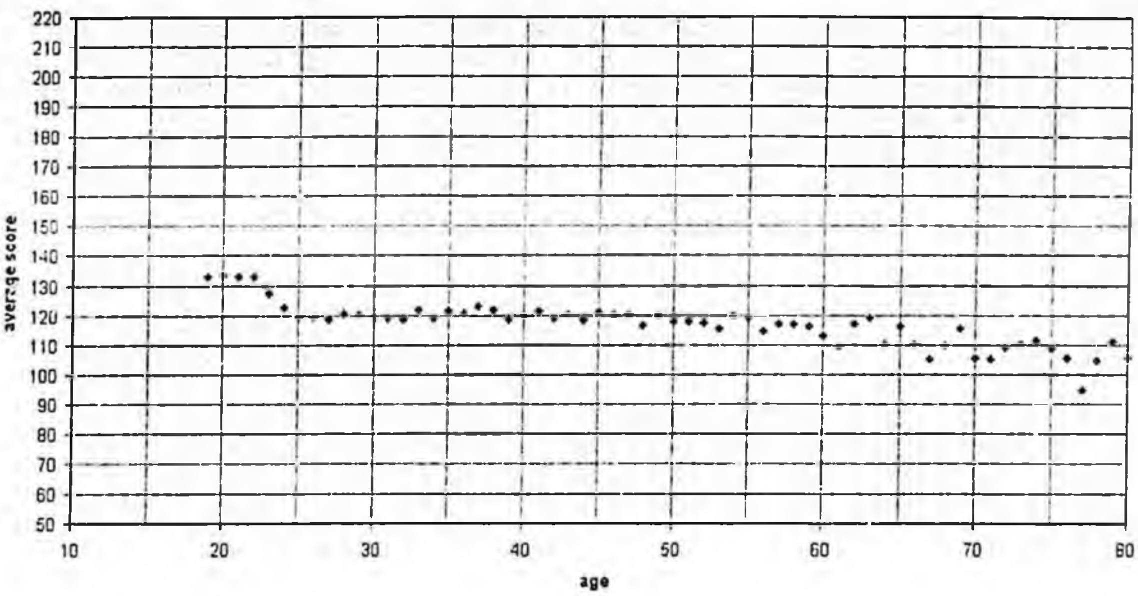
Recently the Alaska Division of Insurance undertook a study "Insurance Credit Scoring in Alaska", to understand how the use of credit history affects different groups of Alaskan insurance consumers. However, since the Division was not provided with the necessary credit data, this is not a study of credit at all. Rather, it is a study of access to Preferred insurance markets.

1. The study found that a disproportionately smaller number of policyholders in lower-income zip codes with higher minority populations qualified for Preferred markets - **regardless of whether or not credit was used to help determine final market.** Furthermore, when credit **was** used, not fewer but **more** of these policyholders actually qualified for the Preferred market. The study reported, "changes in classification of business between preferred, standard, and nonstandard business, may be due, at least in part, to the use of credit history."

2. With regard to access to Preferred markets by age, the study found that the proportion of policyholders in Preferred markets actually peaks for Alaskans aged 61 to 70 years old. Over half of policyholders in this age group are in Preferred markets, well above younger aged policyholders. Conversely, the proportion of policyholders in Non-standard markets is lowest for policyholders aged 61 to 90. These findings are consistent with internal Progressive data - the average age of Alaskan policyholders in Progressive's best credit tier is 43 years - older than any other credit tier. It is the population of older Alaskan drivers, those who have worked hard their whole lives to establish and maintain good credit, who stand to lose the most if the use of credit for insurance underwriting is restricted or banned by the legislature.

   The following chart of over 23,000 policies quoted in Alaska during the first half of 2002 shows that average credit score improves with age (that is, gets lower under the Progressive scoring system).

23,990 AK quotes from first half of 2002, re-scored with AZ1 method



3. Finally, the findings of the study support industry claims that credit has enabled them to write more business and renew more policies. "In the aggregate ... the number of policyholders increased by approximately 8% from 1999 to 2001." This is consistent with Progressive's experience when credit was introduced in Alaska and other states. In addition, Progressive also finds that more often than not, policyholders pay less as a result of their credit history, not more.

Regrettably, these findings are overlooked in the Recommendations and Conclusions of the Report, and are being overlooked by the media and certain legislators. To interpret the results of this research as evidence that credit unfairly discriminates against minority populations, the poor, and the elderly, is to simply ignore the study's own findings.

We recognize, and the Report acknowledges, that there are shortcomings in the research methodology, (largely due to the absence of necessary credit data). For this reason, we agree that caution should be exercised when interpreting the results of this research. The subject of credit is too important to both insurers and Alaskan drivers for hasty legislation based on the results of this research alone.

Progressive conducted an analysis of our policyholders in Alaska comparing the credit scores of high population density areas vs. low population density. Our review showed that while the average credit score changed little across population density, rural areas had slightly better average scores than urban areas.

Reasons why Progressive is opposed to SB 13

Progressive opposes SB 13 because it calls for an outright ban on the use of credit for insurance for personal and commercial insurance in Alaska.

There are significant downsides that can result from an outright ban on credit:

1. An outright ban of credit creates an uneven playing field for local Alaska agents and the insurance companies that write through them. Many direct and captive companies use credit to prescreen mailing lists. If the use of credit were to be eliminated or unreasonably restricted at the state level, the Federal Fair Credit Reporting Act (FCRA) would still permit these companies to prescreen lists for solicitation. This would give these companies a competitive advantage over local Alaska agents by allowing them to specifically target – and write – more profitable, lower priced business.

2. The FCRA preempts state laws attempting to limit the use of credit information to make prescreened insurance offers and would also most likely prevail over state laws precluding the use of credit information for insurance rating or underwriting.

3. An outright ban of the use of credit in insurance will result in less accurate pricing with rate subsidization of good drivers by bad drivers. Large numbers of consumers who currently benefit from the use of credit will see increases in their premiums. Our estimate is that two thirds or over 11, 000 of our current policyholders might see premiums go up as a result of the elimination of the use of credit.

4. Although credit has been recently under review by many state legislatures in other parts of the country, no state has passed an outright ban on the use of credit in auto insurance over the past five years. Many states have created new laws or administrative rules with reasonable regulations on the use of credit, but no outright ban has been passed for auto insurance. Passing such a law in Alaska will create a disadvantage for both Alaska agents and for consumers.

Progressive is committed to working with state legislators and regulators to find common ground that results in reasonable regulation of the use of credit. Progressive supports the Model Credit Act adopted by the National Council of Insurance Legislators as one example of reasonable and responsible disclosure requirements and limitations on the use of credit in insurance. We would support an approach that uses some of the elements of this Model to address the specific concerns over the use of credit in Alaska.

The problem we face is not the use of credit information for insurance, but rather how they are used. Progressive is ready to work with you to help craft responsible reforms that protect our agents and consumers in the state of Alaska.

Thank you for the opportunity to provide my input to your committee.

Mark Niehaus
Agency General Manager
Progressive Companies

Frank H. Murkowski, Governor

Alaska Department of Community and Economic Development

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March 25, 2003

Representative Bruce Weyhrauch
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Juneau, Alaska 99801

MAR 27 2003

Dear Representative Weyhrauch:

As you requested, I would like to provide information on the history of complaints to the Division of Insurance regarding the use of Credit Scoring and what the department has done to address those complaints.

We get many calls in the Consumer Services section dealing with credit scoring. Consumers are always advised by the CSS specialist to file a complaint. They are advised that their situation is unique and they will be dealt with individually by the responding insurer. Relatively few consumers follow through and actually file a formal complaint. It would be fair to estimate that each complaint filed represents another 70-100 consumers facing the same issue but who didn't take the time to file a complaint. This hesitancy to file a complaint could be explained by a number of factors.

1) Consumers may not know the Division of Insurance exists.
2) They don't know about the consumer services available to them at the division.
3) They are intimidated about challenging an insurance company.
4) They feel hopeless and don't challenge their circumstances.
5) They believe the company could retaliate against them by canceling their coverage if they complained. They hesitate to "rock the boat."
6) They don't have confidence in their ability to write their complaint.
7) They presumed their rate increase was justified by their credit score.

The following complaint files are representative of the types of issues consumers are facing with the credit scoring issue.

COMPLAINTS
Example 1: Premium increased from $341 to $736 semi-annually. No prior claims, no record of citations. They felt this was discrimination and something should be done about it. Company said state required update every two years and their credit report was the cause for the increase. Company responded that there was a significant change in point value (credit score) the rating market was changed from Ultra to Standard and that a general rate increase was also applied. No violation was identified.

Example 2: A substantial increase in renewal premium. Company responded that the Increase was due to changes found upon ordering a new Financial Responsibility (credit score.) A significant change in point value (credit score) impacted the renewal rate, causing the rating market to be amended from Ultra Preferred to Middle Market. In addition there was a general rate increase that was applied to his renewal premium. The premium increased from $311 to $782 semi-annually. No violation was identified.
Example 3: Current carrier Increased annual premium from $1500 to $4300 based on their credit score. Complainant switched from current carrier to new company. They were told to call Experian and check their credit rating. They did and it was very good. Company said they had a bad score because they had too many requests for credit ratings, one outstanding bad debt (a disputed issue) and too much activity with credit cards. They pay all credit cards in full every month. They believe credit scoring companies only have knowledge about liabilities not assets. They do not like being generalized and lumped into an inferior category based upon statistics. They changed companies because they felt their company was not interested in them as individuals, only numbers. Company responded by explaining the reason for the increase was due to changes found upon ordering a new financial responsibility (credit score.) No violation was identified. No violation was identified.
Example 4: Insured's premium increased from $448 to $836 for 6 months increase due to credit score. Insured called company's 800 number and was told increase was due to across-the-board increase and insured's credit score. Insured's credit score caused a change from preferred to non-standard. Insured changed to another company at about $6 more a month than previous rate. When insured called to cancel the policy, the previous carrier related that it was an across the board increase and not due to insured's credit score. Insured still cancelled the policy and changed insurers. The insured doesn't understand why high risk drivers with accidents, etc., in non-standard category get a cheaper rate and go the preferred category based on a good credit report, and that non-risk drivers, no accidents, safe driver, etc., go from preferred to non-standard and get to pay more because of their credit report "?????" Insured does not feel that credit score has any bearing on driving abilities or paying for car insurance in a timely fashion. No violation was identified.
Example 5: Rate increase, mid-term four months into 6-month policy. Premium went from $189.83 to $338.75 per month. Company said insured was downgraded from an "A" category to a "D" category because of credit score. Insured furnished us with a copy of their credit report and it is very good. Another person told him it was due to a general rate increase. He was told that neither his driving record nor credit report had anything to do with increase. Company said increase was because DOI told them to reevaluate policyholders for the last two years, so if he has a problem he needs to talk to us. He feels it is unfair discrimination. He wants to know why he is being required to pay more than the amount quoted for the policy period. His coverage ended 4/16/01, about one month prior to end of policy period. Company responded to our complaint by making an exception and amending the policy market to that of the prior policy term, reducing his premium from $1,981 to $1,114 semi-annually. He called to say he found other coverage at less than his old premium and that his credit rating was "B". No violation was identified

Although no violations were identified, the division established a task force that reviewed all aspects of the companies handling of each complaint to ensure compliance with current laws.

We are always pleased to be of assistance to your office. Please do not hesitate to call on us if you need additional information.

Sincerely,

Linda S. Hall

Linda S. Hall
Director

WORK DRAFT WORK DRAFT WORK DRAFT

22-LS1462\T
Ford
4/30/02

CS FOR SENATE BILL NO. 320( )

IN THE LEGISLATURE OF THE STATE OF ALASKA

TWENTY-SECOND LEGISLATURE - SECOND SESSION

BY

Lessmeier & Winters

Offered:
Referred:

MAY - 1 2002

Sponsor(s): SENATOR COWDERY

Received by Fax

A BILL

FOR AN ACT ENTITLED

"An Act relating to using credit history or credit scoring for insurance purposes; and providing for an effective date."

BE IT ENACTED BY THE LEGISLATURE OF THE STATE OF ALASKA:

* **Section 1.** AS 21.36 is amended by adding a new section to read:

Sec. 21.36.460. Restrictions on credit history or credit scoring applicable to personal insurance. (a) An insurer may not use credit scoring in the underwriting process unless the insurer or the insurer's agent obtains oral or written permission from the applicant.

(b) An insurer that takes adverse action involving personal insurance against a consumer based in whole or in part on credit history or credit scoring shall provide written notice to the applicant or named insured. The notice must state the significant factors of the credit history or credit score that resulted in the adverse action and provide information on how credit scores can be improved. The insurer shall also inform the consumer that the consumer is entitled to a free copy of the consumer's report under 15 U.S.C. 1681 (Fair Credit Reporting Act) and provide the consumer with the opportunity to identify errors in the consumer's credit score and to request reconsideration of the adverse action by the insurer.

(c) An insurer may use credit history to deny personal insurance only in combination with other substantive underwriting factors. For the purposes of this subsection,

(1) refusal to offer personal insurance coverage to a consumer constitutes denial of personal insurance; and

(2) an offer of placement with an affiliate insurer does not constitute denial of coverage.

(d) Notwithstanding (c) of this section, an insurer may reject an application when coverage is not bound or cancel an insurance contract within the first 60 days after the effective date of the contract.

(e) An insurer may not deny personal insurance coverage based in whole or in part on the absence of credit history or the inability to determine the consumer's credit history if the insurer has received accurate and complete information from the consumer.

(f) If disputed credit history is used to determine eligibility for personal insurance coverage and a consumer is placed with an affiliate that charges higher premiums or offers less favorable policy terms, the insurer shall reissue or rerate the policy retroactive to the effective date of the current policy term and the policy, as reissued or rerated, shall provide premiums and policy terms the consumer would have been eligible for if accurate credit history had been used to determine eligibility. This subsection only applies if the consumer resolves the dispute under the process in 15 U.S.C. 1681 (Fair Credit Reporting Act) and notifies the insurer in writing that the dispute has been resolved.

(g) In this section,

(1) "adverse action" has the meaning given in 15 U.S.C. 1681 (Fair Credit Reporting Act) and also includes

(A) cancellation, denial, or failure to renew personal insurance coverage;

(B) charging a higher insurance premium for personal insurance than would have been offered if the credit history or credit score had been more favorable, whether the charge is by

(i) application of a rating rule;

(ii) assignment to a rating tier that does not have the lowest available rates; or

(iii) placement with an affiliate company that does not offer the lowest rates available to the consumer within the affiliate group of credit companies; or

(C) any reduction or adverse or unfavorable change in the terms of coverage or amount of personal insurance due to a consumer's credit history or credit score;

(2) "affiliate" has the meaning given in AS 21.22.200;

(3) "consumer" means an individual policyholder or applicant for insurance;

(4) "consumer report" has the meaning given in 15 U.S.C. 1681 (Fair Credit Reporting Act);

(5) "credit history" means written, oral, or other communication of information by a consumer reporting agency bearing on a consumer's creditworthiness, credit standing, or credit capacity that is used or expected to be used, or collected in whole or in part, for the purpose of serving as a factor in determining personal insurance premiums or eligibility for coverage;

(6) "credit score" means a number or rating that is derived from an algorithm, computer application, model, or other process that is based in whole or in part on credit history;

(7) "personal insurance" means

(A) private passenger automobile coverage;

(B) homeowner coverage, including mobile homeowner's, manufactured homeowner's, condominium owner's, and renter's coverage;

(C) dwelling property coverage;

(D) earthquake coverage for a residence or personal property;

(E) personal liability and theft coverage;

(F) personal inland marine coverage;

(G) mechanical breakdown coverage for personal auto or home appliances; and

(H) flood insurance;

(8) "tier" means a category within a single insurer into which insureds with substantially like insuring, risk or exposure factors, and expense elements are placed for purposes of determining rate or premium.

*** Sec. 2.** AS 21.39 is amended by adding a new section to read:

Sec. 21.39.035. Making of rates; personal insurance. (a) If requested by the director, an insurer that uses a credit scoring model shall file with the director the credit scoring model, including data that supports the validity of the model, used to determine personal insurance rates, premiums, or eligibility for coverage. The credit scoring model must include all attributes and factors used in the calculation of a credit score.

(b) Information filed under (a) of this section

(1) is confidential, and the information is not subject to public inspection under AS 21.39.040(a);

(2) shall be considered a trade secret under AS 45.50.910;

(3) may be made public by the director for the sole purpose of enforcement actions taken by the director; and

(4) may be disclosed by the insurer that files the information.

(c) An insurer may not use the following types of credit history to calculate a credit score or determine personal insurance premiums or rates:

(1) the absence of credit history or the inability to determine the consumer's credit history unless the insurer has filed actuarial data segmented by demographic factors in a manner proscribed by the director that demonstrates compliance with AS 21.39.030;

(2) methodology that incorporates gender, race, nationality, or religion;

(3) credit history or a credit score that results in unfair discrimination;

(4) the number of credit inquiries; this paragraph does not apply if the

consumer makes more than one inquiry in a 30-day period about automobile or mortgage financing; in this paragraph, "automobile or mortgage financing" does not include marketing, promotional, or insurance inquiries;

(5) credit history or a credit score based on collection accounts identified with a medical industry code;

(6) the consumer's total available line of credit; however, an insurer may consider the total amount of outstanding debt in relation to the total available line of credit.

(d) If a consumer is charged higher premiums due to disputed credit history, the insurer shall rerate the policy retroactive to the effective date of the current policy term. As rerated, the consumer shall be charged the same premiums that would have been charged if the accurate credit history was used to calculate a credit score. This subsection only applies if the consumer resolves the dispute under the process in 15 U.S.C. 1681 (Fair Credit Reporting Act) and notifies the insurer in writing that the dispute has been resolved.

(e) In this section,

(1) "consumer" means an individual policyholder or applicant for insurance;

(2) "credit history" has the meaning given in AS 21.36.460;

(3) "credit score" has the meaning given in AS 21.36.460;

(4) "personal insurance" has the meaning given in AS 21.36.460.

* Sec. 3. AS 21.36.460 and AS 21.39.035 are repealed July 1, 2006.

* Sec. 4. This Act takes effect January 1, 2003.

NATIONAL CONFERENCE OF INSURANCE LEGISLATORS

MODEL ACT REGARDING USE OF CREDIT INFORMATION IN PERSONAL INSURANCE

Adopted by the NCOIL Property-Casualty Insurance and Executive Committees on November 22, 2002.

Table of Contents

Section 1. Short Title

This Act may be called the *Model Act Regarding Use of Credit Information in Personal Insurance.*

Section 2. Purpose

The purpose of this Act is to regulate the use of credit information for personal insurance, so that consumers are afforded certain protections with respect to the use of such information.

Section 3. Scope

This Act applies to personal insurance and not to commercial insurance. For purposes of this Act, "personal insurance" means private passenger automobile, homeowners, motorcycle, mobile-homeowners and non-commercial dwelling fire insurance policies [and boat, personal watercraft, snowmobile and recreational vehicle polices]. Such policies must be individually underwritten for personal, family or household use. No other type of insurance shall be included as personal insurance for the purpose of this Act.

Section 4. Definitions

For the purposes of this Act, these defined words have the following meaning:

A. Adverse Action—A denial or cancellation of, an increase in any charge for, or a reduction or other adverse or unfavorable change in the terms of coverage or amount of, any insurance, existing or applied for, in connection with the underwriting of personal insurance.

B. Affiliate—Any company that controls, is controlled by, or is under common control with another company.

C. Applicant—An individual who has applied to be covered by a personal insurance policy with an insurer.

D. Consumer—An insured whose credit information is used or whose insurance score is calculated in the underwriting or rating of a personal insurance policy or an applicant for such a policy.

E. Consumer Reporting Agency—Any person which, for monetary fees, dues, or on a cooperative nonprofit basis, regularly engages in whole or in part in the practice of assembling or evaluating consumer credit information or other information on consumers for the purpose of furnishing consumer reports to third parties.

F. Credit Information—Any credit-related information derived from a credit report, found on a credit report itself, or provided on an application for personal insurance. Information that is not credit-related shall not be considered "credit information," regardless of whether it is contained in a credit report or in an application, or is used to calculate an insurance score.

G. Credit Report—Any written, oral, or other communication of information by a consumer reporting agency bearing on a consumer's credit worthiness, credit standing or credit capacity which is used or expected to be used or collected in whole or in part for the purpose of serving as a factor to determine personal insurance premiums, eligibility for coverage, or tier placement.

H. Insurance Score—A number or rating that is derived from an algorithm, computer application, model, or other process that is based in whole or in part on credit information for the purposes of predicting the future insurance loss exposure of an individual applicant or insured.

Section 5. Use of Credit Information

An insurer authorized to do business in *[insert State]* that uses credit information to underwrite or rate risks, shall not:

A. Use an insurance score that is calculated using income, gender, address, zip code, ethnic group, religion, marital status, or nationality of the consumer as a factor.

B. Deny, cancel or nonrenew a policy of personal insurance solely on the basis of credit information, without consideration of any other applicable underwriting factor independent of credit information and not expressly prohibited by Section 5(A).

C. Base an insured's renewal rates for personal insurance solely upon credit information, without consideration of any other applicable factor independent of credit information.

D. Take an adverse action against a consumer solely because he or she does not have a credit card account, without consideration of any other applicable factor independent of credit information.

E. Consider an absence of credit information or an inability to calculate an insurance score in underwriting or rating personal insurance, unless the insurer does one of the following:

   1. Treat the consumer as otherwise approved by the Insurance Commissioner/ Supervisor/Director, if the insurer presents information that such an absence or inability relates to the risk for the insurer.

   2. Treat the consumer as if the applicant or insured had neutral credit information, as defined by the insurer.

   3. Exclude the use of credit information as a factor and use only other underwriting criteria.

F. Take an adverse action against a consumer based on credit information, unless an insurer obtains and uses a credit report issued or an insurance score calculated within 90 days from the date the policy is first written or renewal is issued.

G. Use credit information unless not later than every 36 months following the last time that the insurer obtained current credit information for the insured, the insurer recalculates the insurance score or obtains an updated credit report. Regardless of the requirements of this subsection:

1. At annual renewal, upon the request of a consumer or the consumer's agent, the insurer shall re-underwrite and re-rate the policy based upon a current credit report or insurance score. An insurer need not recalculate the insurance score or obtain the updated credit report of a consumer more frequently than once in a twelve-month period.

2. The insurer shall have the discretion to obtain current credit information upon any renewal before the 36 months, if consistent with its underwriting guidelines.

3. No insurer need obtain current credit information for an insured, despite the requirements of subsection (G)(1). if one of the following applies:

   (a) The insurer is treating the consumer as otherwise approved by the Commissioner.

   (b) The insured is in the most favorably-priced tier of the insurer, within a group of affiliated insurers. However, the insurer shall have the discretion to order such report, if consistent with its underwriting guidelines.

   (c) Credit was not used for underwriting or rating such insured when the policy was initially written. However, the insurer shall have the discretion to use credit for underwriting or rating such insured upon renewal, if consistent with its underwriting guidelines.

   (d) The insurer re-evaluates the insured beginning no later than 36 months after inception and thereafter based upon other underwriting or rating factors, excluding credit information.

H. Use the following as a negative factor in any insurance scoring methodology or in reviewing credit information for the purpose of underwriting or rating a policy of personal insurance:

1. Credit inquiries not initiated by the consumer or inquiries requested by the consumer for his or her own credit information.

2. Inquiries relating to insurance coverage, if so identified on a consumer's credit report.

3. Collection accounts with a medical industry code, if so identified on the consumer's credit report.

4. Multiple lender inquiries, if coded by the consumer reporting agency on the consumer's credit report as being from the home mortgage industry and made within 30 days of one another, unless only one inquiry is considered.

5. Multiple lender inquiries, if coded by the consumer reporting agency on the consumer's credit report as being from the automobile lending industry and made within 30 days of one another, unless only one inquiry is considered.

Section 6. Dispute Resolution and Error Correction

If it is determined through the dispute resolution process set forth in the federal Fair Credit Reporting Act, 15 USC 1681i(a)(5), that the credit information of a current insured was incorrect or incomplete and if the insurer receives notice of such determination from either the consumer reporting agency or from the insured, the insurer shall re-underwrite and re-rate the consumer within 30 days of receiving the notice. After re-underwriting or re-rating the insured, the insurer shall make any adjustments necessary, consistent with its underwriting and rating guidelines. If an insurer determines that the insured has overpaid premium, the insurer shall refund to the insured the amount of overpayment calculated back to the shorter of either the last 12 months of coverage or the actual policy period.

Section 7. Initial Notification

A. If an insurer writing personal insurance uses credit information in underwriting or rating a consumer, the insurer or its agent shall disclose, either on the insurance application or at the time the insurance application is taken, that it may obtain credit information in connection with such application. Such disclosure shall be either written or provided to an applicant in the same medium as the application for insurance. The insurer need not provide the disclosure statement required under this section to any insured on a renewal policy, if such consumer has previously been provided a disclosure statement.

B. Use of the following example disclosure statement constitutes compliance with this section: "In connection with this application for insurance, we may review your credit report or obtain or use a credit-based insurance score based on the information contained in that credit report. We may use a third party in connection with the development of your insurance score."

Section 8. Adverse Action Notification

If an insurer takes an adverse action based upon credit information, the insurer must meet the notice requirements of both (A) and (B) of this subsection. Such insurer shall:

A. Provide notification to the consumer that an adverse action has been taken, in accordance with the requirements of the federal Fair Credit Reporting Act, 15 USC 1681m(a).

B. Provide notification to the consumer explaining the reason for the adverse action. The reasons must be provided in sufficiently clear and specific language so that a person can identify the basis for the insurer's decision to take an adverse action. Such notification shall include a description of up to four factors that were the primary influences of the adverse action. The use of generalized terms such as "poor credit history," "poor credit rating," or "poor insurance score" does not meet the explanation requirements of this subsection. Standardized credit explanations provided by consumer reporting agencies or other third party vendors are deemed to comply with this section.

Section 9. Filing

A. Insurers that use insurance scores to underwrite and rate risks must file their scoring models (or other scoring processes) with the Department of Insurance. A third party may file scoring models on behalf of insurers. A filing that includes insurance scoring may include loss experience justifying the use of credit information.

B. Any filing relating to credit information is considered trade secret under *[cite to the appropriate state law]*.

Section 10. Indemnification

An insurer shall indemnify, defend, and hold agents harmless from and against all liability, fees, and costs arising out of or relating to the actions, errors, or omissions of [an agent / a producer] who obtains or uses credit information and/or insurance scores for an insurer, provided the [agent / producer] follows the instructions of or procedures established by the insurer and complies with any applicable law or regulation. Nothing in this section shall be construed to provide a consumer or other insured with a cause of action that does not exist in the absence of this section.

Section 11. Sale of Policy Term Information by Consumer Reporting Agency

A. No consumer reporting agency shall provide or sell data or lists that include any information that in whole or in part was submitted in conjunction with an insurance inquiry about a consumer's credit information or a request for a credit report or insurance score. Such information includes, but is not limited to, the expiration dates of an insurance policy or any other information that may identify time periods during which a consumer's insurance may expire and the terms and conditions of the consumer's insurance coverage.

B. The restrictions provided in subsection (A) of this section do not apply to data or lists the consumer reporting agency supplies to the insurance [agent / producer] from whom information was received, the insurer on who's behalf such [agent / producer] acted, or such insurer's affiliates or holding companies.

C. Nothing in this section shall be construed to restrict any insurer from being able to obtain a claims history report or a motor vehicle report.

Section 12. Severability

If any section, paragraph, sentence, clause, phrase, or any part of this Act passed is declared invalid due to an interpretation of or a future change in the federal Fair Credit Reporting Act, the remaining sections, paragraphs, sentences, clauses, phrases, or parts thereof shall be in no manner affected thereby but shall remain in full force and effect.

Section 13. Effective Date

This Act shall take effect on *[insert date]*, applying to personal insurance policies either written to be effective or renewed on or after 9 months from the effective date of the bill.

BUREAU OF
BUSINESS
RESEARCH

A Statistical Analysis of the Relationship Between Credit History and Insurance Losses

Prepared by: Bureau of Business Research
McCombs School of Business
The University of Texas at Austin

March 2003

A Statistical Analysis of the Relationship Between Credit History and Insurance Losses

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Bureau of Business Research
The University of Texas at Austin
March 2003

About the Bureau of Business Research

Research and services at the Bureau of Business Research (BBR) focus on the competitiveness of Texas industries. By providing essential research and information about Texas industries, the BBR has linked the academic community and the public since 1927. Located within the McCombs School of Business at The University of Texas at Austin, the BBR conducts applied economic research on the organizational and resource strategies of Texas industries, with an emphasis on the high-technology sector. The BBR also houses significant information resources through its affiliation with the State Data Center Program and the U.S. Bureau of the Census. For more information, please visit the BBR website at www.utexas.edu/depts/bbr/.

Acknowledgements

Appreciation is expressed to the insurance company representatives who participated in or facilitated the study. Other individuals who provided valuable assistance include Janice Steffes, Denise Davis, Steve Collins, and Bill Paxton. Thanks also to BBR staff members Julia Apodaca, Dorothy Brady, and Sally Furgeson for their help in preparing the report.

A Statistical Analysis of the Relationship Between Credit History and Insurance Losses

Executive Summary

At the request of Lt. Governor Bill Ratliff in 2002, the Bureau of Business Research (BBR) examined the relationship between credit history and insurance losses in automobile insurance. With the assistance of the leading automobile insurers in Texas, the BBR research team constructed a database of automobile insurance policies from the first quarter of 1998 that included the following 12 months' premium and loss history. Choicepoint, a commercial firm that provides underwriting information products for the U. S. property and casualty personal lines insurance market, then matched the named insured on the policy with his or her credit history and supplied a "credit score" using an insurance credit scoring methodology it markets to automobile insurers. This credit score and its relationship with prospective losses for the policy were then examined.

Using logistic and multiple regression analyses, the research team tested whether the credit score for the named insured on a policy was significantly related to incurred losses for that policy. It was determined that there was a significant relationship. In general, lower credit scores were associated with larger incurred losses. Next, logistic and multiple regression analyses examined whether the revealed relationship between credit score and incurred losses was explainable by existing underwriting variables, or whether the credit score added new information about losses not contained in the existing underwriting variables. It was determined that credit score did yield new information not contained in the existing underwriting variables.

What the study does not attempt to explain is why credit scoring adds significantly to the insurer's ability to predict insurance losses. In other words, causality was not investigated. In addition, the research team did not examine such variables such as race, ethnicity, and income in the study, and therefore this report does not speculate about the possible effects that credit scoring may have in raising or lowering premiums for specific groups of people. Such an assessment would require a different study and different data.

A Statistical Analysis of the Relationship Between Credit History and Insurance Losses

Introduction

Over the past decade, the insurance industry has begun using credit histories to create "credit scores" for individuals who apply for, or renew, automobile insurance policies. These scores ("high" if a person's credit history is good, "low" if it is not good) are then used in rate-making decisions, presumably raising premiums for individuals with poor credit history and lowering premiums for those with good credit history. Additionally, such scores may be used by some insurers in underwriting procedures, including placement of policyholders within insurance company groups, or even in denying or canceling insurance.[1]

There is a public policy debate over whether a statistically significant relationship exists between credit history and insurance loss, and the debate concerns not only the existence of such a relationship, but also the effect that the use of credit scoring might have on various subgroups of the population. The insurance industry has conducted or sponsored a number of studies that claim to demonstrate that, statistically, the poorer an individual's credit history, the higher the expected losses that the individual will generate for the insurance company, thereby justifying a higher premium for people with poorer credit histories and a lower premium for people with better credit histories. Consumer groups have questioned the basis of this alleged relationship and assert that there is no relationship between an individual's credit history and the propensity to file insurance claims. Additionally, others maintain that if there is a relationship, it is due to other variables and that no underlying causal or direct link exists.

In the summer of 2002, then-Lt. Governor Ratliff asked the Bureau of Business Research (BBR), as a nonpartisan and independent research unit, to investigate whether a statistically significant relationship exists between credit score and insurance loss and to report the result of the investigation to the Legislature. To effect this assessment, a random sample of automobile insurance policies, including loss histories, premiums, and other variables, were obtained from several of the largest companies writing automobile insurance coverage in Texas. These policies were then matched with the credit history of the named insured on the policy to create a database including both policy information and credit information (including a summary "credit score"). Information about race, ethnicity, or income was not included in the data collected by the BBR for the study, and consequently no conclusions will be drawn about the effect of credit scoring on various racial, ethnic, or income sub-groups in the population.

Methodology

In order to establish whether a statistically significant relationship exists between a person's credit history and his or her potential to produce insurance losses, it was necessary to match a large database of insurance policies with the corresponding credit histories of the named insured

[1] A company group is a collection of insurance companies sharing the same managerial control. For example, some company groups have both a standard market subsidiary company and a county mutual (non-standard market) subsidiary company. These two companies would be considered part of the same company group.

in each policy. Then, controlling for other underwriting characteristics such as age, gender, prior driving record, and vehicle type, multivariate regression analyses were used to test whether adding credit information to a variety of other underwriting characteristics improved the accuracy of loss prediction.

In this study, insurance companies selling in the Texas automobile market were ranked according to the amount of their premiums written in the state. The insurers comprising the top 70 percent of the market (in descending order, starting with the largest companies) were then asked to provide a random sample of new or renewing automobile policies from the first quarter of 1998 (January 1, 1998 through March 31, 1998). This examination period was chosen chiefly for two reasons. First, most of the insurers from whom data were requested were not using credit scoring at that time in rate-making or underwriting decisions, which meant that premium data collected were not affected by credit history. Second, loss information, including paid losses and reserves for losses, could be obtained for a one-year period with ease. Even slow-paying claims would then have some chance of being recorded in the database. Five insurers, including those with both standard and non-standard subsidiaries (county mutuals), supplied data for the study, with the number of policies produced by each insurer corresponding to its market share. (For example, if Insurer A had a 10 percent market share of the dollar value of premiums written in Texas, it was asked for a number of policies that would total 10 percent of the resulting sample.) Data on the following variables were requested from the insurers:[2]

- Age of insured
- Gender of insured
- Marital status of insured
- Location where automobile(s) driven
- Use of automobile(s) (i.e., business use, pleasure, to and from work)
- Prior driving record of insured drivers
- Annual mileage driven
- Make and model of automobile(s) covered
- Age of automobile(s)
- Premium[3]
- Incurred losses[4]

A total of 175,647 separate policies were submitted by the participating insurance companies and transferred to a commercial firm (Choicepoint) that provides underwriting information products for the U. S. property and casualty personal lines insurance market. Choicepoint obtained the credit history for the policies' named insured by matching on name, address, or Social Security number. (Such individual identifying characteristics were removed from the data by Choicepoint prior to transmittal to the BBR.) Of the policies transferred to Choicepoint, 22,321 (12.7 percent) did not have sufficient or matchable information or credit history to create a credit score.[5] Thus, the final database contained 153,326 policies with credit scores matched and 22,321 without credit scores. For non-standard market insurance company (county mutual) data, the "no-hit" rate was slightly higher (at 14.4 percent) than for standard insurance market company data (12.3

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[2] Not all companies provided all requested information.
[3] Premium data were for exactly one year of coverage from policy inception or renewal date.
[4] Incurred losses included actual losses and reserves for losses for a 12-month period after the inception or renewal date in the first quarter of 1998.
[5] Choicepoint did not go to secondary or tertiary credit vendors to try to increase the "hit" rate. This was partially due to time and financial constraints, but also because a consistent data record for each named insured was needed to perform tests on the data.

percent), which may be because of the "safety valve role" that the non-standard market insurers play in the proper functioning of the automobile insurance market in Texas.[6]

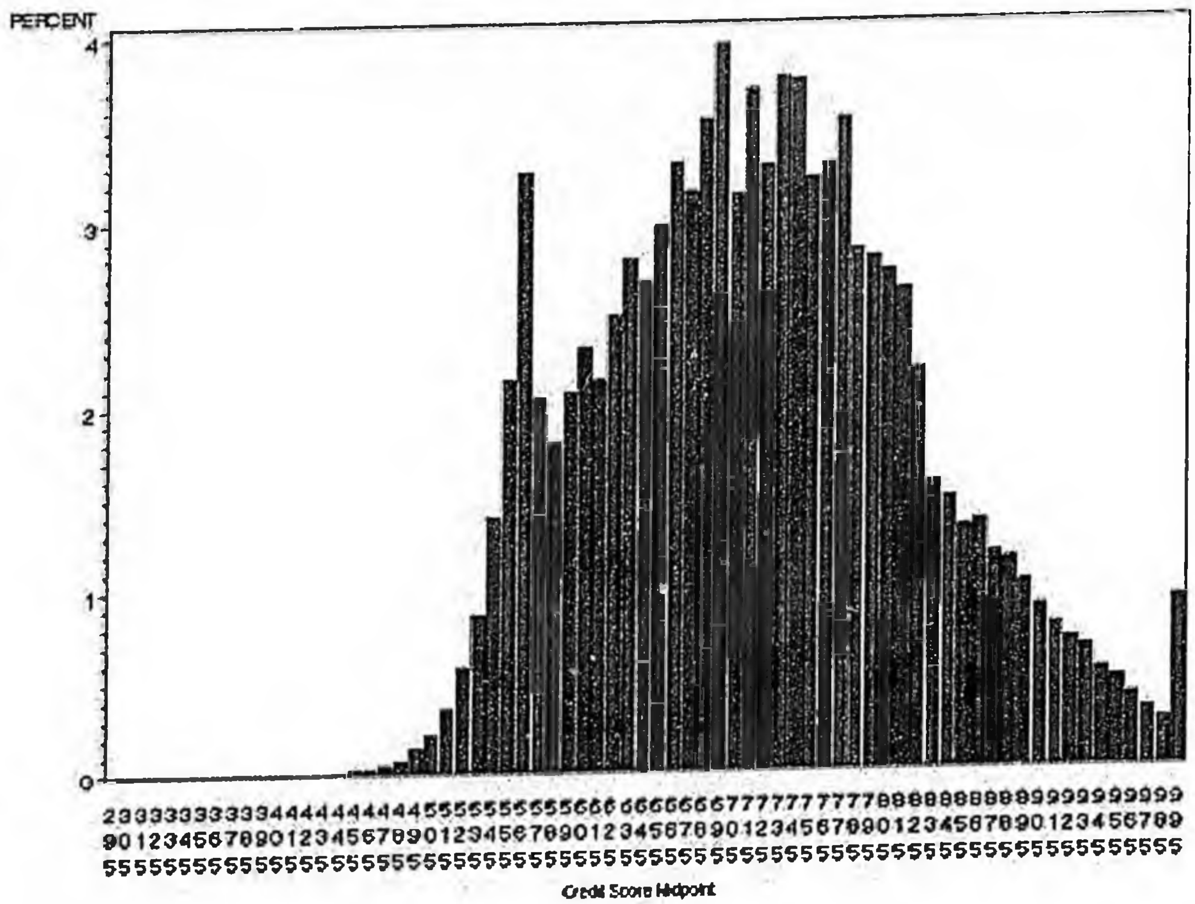
Choicepoint's credit data on each named insured included a total of 445 credit variables along with a summary "credit score" created by Choicepoint.[7] Charts 1, 2, and 3 contain distributions of credit scores in the database. The distribution of credit scores within an insurer's clientele (also known as an insurer's "book of business") will vary according to the strategic plan of the insurer. Chart 1 shows the distribution of scores for the entire sample of policies from both standard and non-standard insurers. Chart 2 shows the distribution of scores for policies from the non-standard insurers participating in the study. Chart 3 shows the distribution of scores for policies from the standard market insurers participating in the study. Credit scores for the standard market (mean=733.0) are significantly higher than the credit scores for the non-standard market (mean=657.7). This most likely represents the safety valve role that the non-standard market insurers play in Texas, providing insurance for those unable to obtain insurance in the standard market.

[6]For more information on the role played by non-standard market companies in Texas, see "An Economic Overview of the County Mutual Insurance Market in Texas," Patrick L. Brockett and Chris Sapstead, Working Paper, Center for Risk Management and Insurance, University of Texas at Austin, 1999.

[7]A credit score typically is a number between 200 and 1000 that reflects the strength of a person's credit history. It is created either by the credit vendor or the insurance company. Many insurance companies use their own algorithms to customize credit scores based on their particular market segments. The score used in this study should not be considered definitive, only representative of scores created by a major vendor in the market.

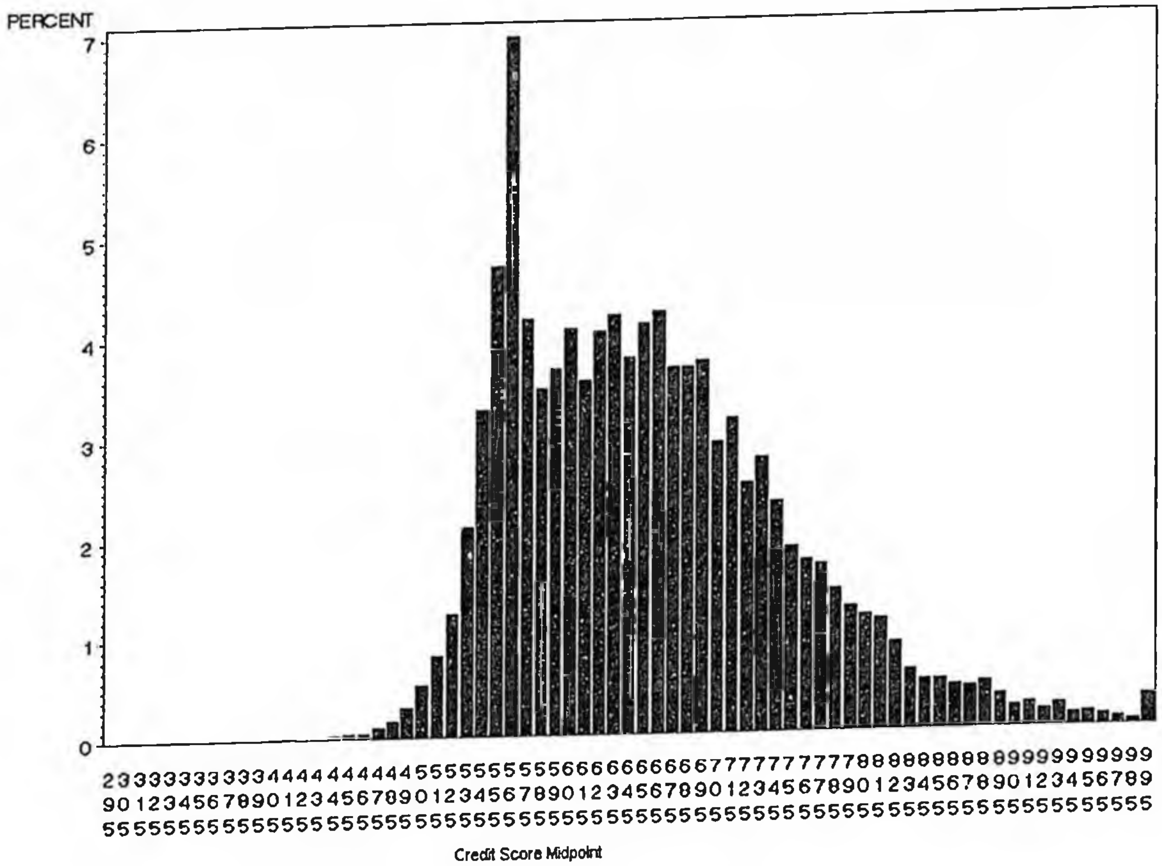
Chart 1

Credit Score Distribution for the Total Market Data Set



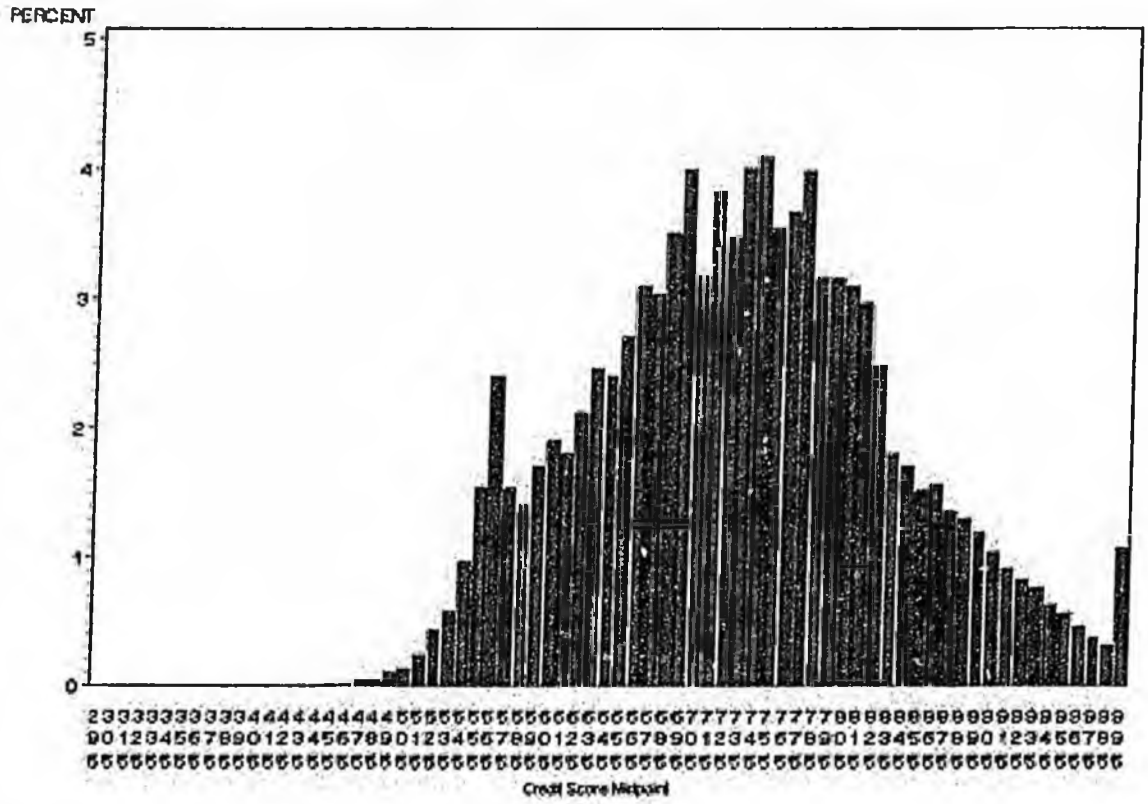
Mean: 719.5
Standard Deviation: 106.9
Range: 295-997
Sample size: 153,326

Chart 2
Credit Score Distribution for the Non-Standard Market Data Set



Mean: 657.7
Standard Deviation: 93.5
Range: 383-997
Sample Size: 29,086

Chart 3
Credit Score Distribution for the Standard Market Data Set



Mean: 733.0
Standard Deviation: 104.6
Range: 295-997
Sample Size: 124,240

Loss Ratio

For every dollar in premiums that automobile insurance companies receive, they plan on spending a certain amount of money to pay claims and loss adjustment expenses. The remaining amount is available for administration costs, taxes, profit, and commissions. The ratio of incurred losses plus loss adjustment expenses to earned premiums is called the **loss ratio** and is a frequently used measure of performance for a group of automobile insurance policies.[8] For the companies writing policies in Texas that were examined in this study, the average individual insurance company loss ratio varied from 58 percent to 74 percent, with an average of 61 percent across all companies in the database. Because different insurers have different underwriting guidelines and different risk profiles for their businesses, the "target" loss ratio will differ from insurer to insurer depending on the strategic positioning and the returns needed to accomplish strategic objectives (i.e., insurers writing higher risk business may strategically require higher rates of return or profit,

[8]Formally, the loss ratio for a policy is defined as the sum of actual paid losses, loss expenses, and loss reserves divided by the earned premium. This ratio takes into account the "best expectation" of the ultimate claim cost for a claim that has not yet fully settled and been paid and the actual premium that has been "earned" in the sense that the coverage was actually provided for the time interval.

resulting in a lower target loss ratio). In a simplified fashion, the insurer sets premiums (using underwriting criteria such as age, type of automobile, coverage, deductible, territory where driven, age and gender of driver, etc.) in such a manner as to accommodate the underwriting characteristics while targeting the insurer's anticipated loss ratio. If the underwriting characteristics for a group of policies indicate that an expected loss will exceed that supported by the premium, then the premium is raised for this group of policies. If the underwriting characteristics indicate that an expected loss will be less than that supported by the premium, then the premium can be lowered until the expected loss ratio is, on the average for the group being priced, equal to the target loss ratio.

Within a given insurer, policies are grouped together according to the underwriting characteristics of the policy with the intent of making policies within a group as homogeneous as possible. For any such group of policies, a loss ratio exactly equal to the insurer's target loss ratio means that the insurance company has correctly priced its premiums for this group to account for the expected losses in that group and the strategic goals of the insurer. A loss ratio for an underwriting group that is greater than the insurer's target loss ratio means that the losses for the group exceed the amount that the premiums can support within the strategic positioning of the insurer. Similarly, a ratio for an underwriting group that is less than the insurer's target loss ratio indicates that premiums were set too high relative to the losses and expenses (including profit) and the insurer's strategic goals (as demonstrated by the loss ratio).

Because of the random nature of individual accidents, it makes sense to only measure the average loss ratio for large groups of policies and not for individual policyholders. (About 80 percent of policies show no claim during a given year and hence have a loss ratio of zero, but the average for a group of policies will be non-zero.) However, some groups of drivers may exhibit higher accident frequencies than other groups and submit claims at a higher rate. For instance, younger drivers tend to have more accidents as a group than older drivers. If premiums were not adjusted upward for younger drivers, the loss ratio for the group would be higher than the target ratio. Theoretically, however, when premiums are raised for younger drivers, the loss ratio for younger drivers as a group adjusts downward. This adjustment process continues until the target loss ratio for an insurance company is achieved. When this occurs, the loss ratio for younger drivers should approximate the loss ratio for older drivers, since increased losses are already compensated for by increased premiums. If done correctly, this adjustment process makes the loss ratio for the insurer constant across all groups of drivers, with no group of drivers being charged premiums disproportionate to its anticipated losses.

In a world with perfect information, the premiums charged by the insurer would be adjusted upward or downward by actuaries to account for increased or decreased loss expectancy for the group of drivers being priced, so that each group has a loss ratio equal to the insurer's target loss ratio. Thus, the expected loss ratio for policies within a class of policies defined by their underwriting characteristics has already, to the best ability of the insurer's actuaries in a cost-effective manner, accounted for underwriting variables such as age, gender, territory driven, deductible, make, model and year of car, number of cars and drivers, and so forth, such that the expected loss ratio of this class will approximate the insurer's target loss ratio. Indeed, if there were systematic deviations from the target loss ratio for a given underwriting class, the premiums for this class would be adjusted to remove this systematic bias. Any variation in loss ratio within the class should be due strictly to random or non-systematic error. Conversely, if an analysis of a particular potential underwriting variable shows that it is significantly related to the loss ratio for the insurer, then this variable's influence on losses has not been accounted for by previous adjustments in premiums, and the inclusion of this variable as another underwriting variable adds value when determining the appropriate premium.

Thus, for a particular insurer, the usefulness of adding an additional underwriting variable beyond those that have already been priced and included can be assessed by ascertaining whether the variable is significantly related to the loss ratio. For example, consider proposed underwriting variable A. The current loss ratio has already incorporated the existing underwriting variables such as age, gender, make, model and year of car, and usage of the automobile, and insurance selections such as coverage amounts and deductibles through adjustments of the premiums. The statistical relationship between proposed underwriting variable A and the loss ratio will reveal whether including variable A into a new underwriting classification scheme is actuarially justified or whether the information underwriting variable A contains is already incorporated into the premium. If the information about losses due to underwriting variable A is already incorporated into the premium, there will be no statistical relationship between the loss ratio and variable A.

Relative Loss Ratio

As mentioned earlier, different insurers have different target markets and different risk profiles, and consequently different target loss ratios. The above discussion implies that for any one particular insurer, the loss ratio incorporates the multitude of underwriting variables and is an appropriate variable for assessing the statistical usefulness of a new potential underwriting variable such as credit score. However, one must be careful when aggregating across insurers. If one insurer or group of insurers had both a lower average credit score for its clientele and a higher average loss ratio than the automobile insurance industry as a whole, then an examination of credit scores versus loss ratios might indicate a relationship due to an insurer effect rather than due to an intrinsic relationship between credit score and loss ratio. The way to avoid this problem is to use a **relative loss ratio** for each policy, where relative loss ratio is defined as the loss ratio for the policy divided by the average loss ratio for the insurer issuing the policy. In this manner, each policy is adjusted to reflect the individual issuing insurer's characteristics. Doing so avoids potentially spurious findings due solely to insurer differences. If there were no insurer differences in target loss ratios, this adjustment would not have any effect on the outcome of the statistical analysis. But if there were differences, using relative loss ratios rather than (absolute) loss ratios for assessing the statistical impact of using credit scoring eliminates this source of bias.

In the analysis that follows, the assessment of the relationship between credit scoring and insurance losses, after accounting for other underwriting variables, will be accomplished by relating the relative loss ratio to the credit score. This will be done for groups of policies. If a group of policies has been priced to reflect the expected losses for the group, then the average relative loss ratio will be 1.0 (i.e., the average loss ratio for members of the group will be the same as the target loss ratio for the issuing insurer).

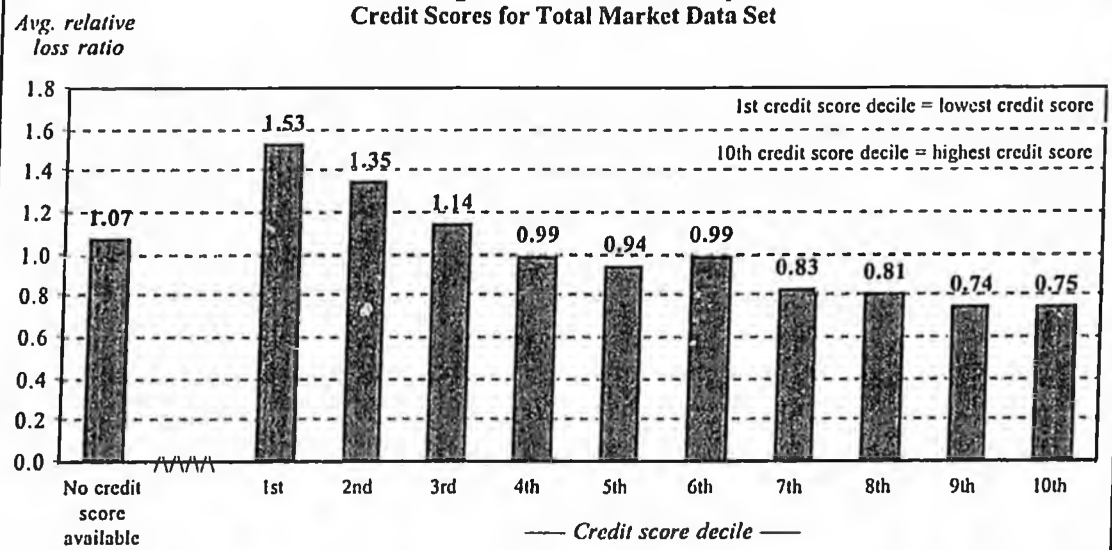
Deleted Files

The database contained a small number of policies that were clearly anomalous and consequently were deleted before undertaking any data analysis. A total of 157 policies and credit histories with the following characteristics were deleted from the database: earned premium equal to or less than zero; incurred loss less than and not equal to zero; or no automobiles or a negative number of automobiles covered during the policy period. In addition, 57 other policies with loss ratios equal to or greater than 100 were deleted. For example, some policies that were deleted in this category were reported to have loss ratios in the hundreds of trillions of dollars. These deletions represent a statistically insignificant percentage (.0012 percent) of all policy records in the database, but an analysis without deleting these anomalous policies affected averages in an unwarranted fashion. The net sample on which tests were conducted was 175,433 policies, of which 22,284 were policies for which there was too little credit information available to generate a credit score (the "no hit group") and 153,149 policies with credit scores matched.

Research Findings

Chart 4 graphically illustrates the main finding of the study. The database of policies was sorted by credit score into ten groups of equal size. (Hereafter, the ten groups are referred to as "deciles.") All but one of the deciles contained 15,315 policies (one decile contained 15,314 policies).[9] The average relative loss ratio is given in Chart 4 for each of ten credit score deciles and the group of policies with no associated credit score.[10] The chart reveals that the three deciles containing policies with the lowest credit scores have average relative loss ratios greater than 1.0. The seven deciles containing policies with the highest credit scores have average relative loss ratios less than 1.0. For the named insureds in the lowest 10 percent of the credit scores, the relative loss ratio for their policies averaged 53 percent higher than expected, whereas for the named insureds within the highest 10 percent of the credit scores, the relative loss ratio averaged 25 percent lower than expected. (Recall that a relative loss ratio of 1.0 is the average or expected relative loss ratio obtained when ignoring credit scoring altogether.) The group of policies with no credit history available has an average loss ratio of 1.07, or 7 percent higher than the average relative loss ratio for the dataset.

Chart 4
Average Relative Loss Ratios By Credit Scores for Total Market Data Set



Statistical analyses confirmed the visual relationship apparent in Chart 4. A regression analysis of the relative loss ratio on credit score was highly significant ($p<.0001$). This indicates that there is less than a 1 in 10,000 chance that the relationship observed between credit score and relative loss ratio could be due to chance alone. Breaking the loss into frequency of loss and severity of loss, two additional analyses were performed. A logistic regression analysis was conducted to determine whether the existence of a positive claim (incurred loss greater than zero) was significantly related to credit score. Each policy was classified as to whether a positive loss or no

[9]The 22,284 policies with no credit score available were placed in their own group and analyzed along with the other ten groups.

[10]The standard deviations of the relative loss ratios for each of the deciles, including the "no credit score available" category, from left to right, are: 6.1, 6.9, 6.3, 5.7, 5.1, 5.3, 5.8, 5.0, 4.9, 4.4, 4.9. Not only does the average relative loss ratio tend to decrease with increasing credit score, but the uncertainty in predicting the relative loss ratio (standard deviation) also tends to decrease with increasing credit score.

loss was experienced. This classification variable was then related to credit score using logistic regression. It was found that there was a statistically significant relationship between credit score and the likelihood of a positive claim being filed ($p<.0001$). Another analysis was performed to ascertain if the size of the claim was related to credit score. For this analysis, a regression of the relative loss ratio on credit score was performed using only those policies having a positive relative loss ratio. Again for this regression the credit score was significant ($p<.0001$), indicating that the size of the loss is also significantly related to credit score. Finally, using the data grouped by credit score deciles exhibited in Chart 4, the correlation between credit score and relative loss ratio was calculated. The correlation (r) was .95, which is statistically and substantively significant. Thus, the analyses show that both the likelihood of a positive claim, and the size of the claim should it occur, are significantly related to credit score, even accounting for other underwriting variables and differences in individual insurance company target loss ratios.

Chart 5 shows the average relative loss ratio distribution for each credit score decile among policies in the sample taken from standard market insurers. The distribution is similar to that shown in Chart 4, with policies in the three lowest credit score deciles showing an average relative loss ratio significantly higher than the seven highest deciles. Again, for the grouped data in Chart 5, the correlation between credit score and relative loss ratio, .95, was highly significant.

Chart 5

Average Relative Loss Ratios By Credit Scores for Standard Market Data Set

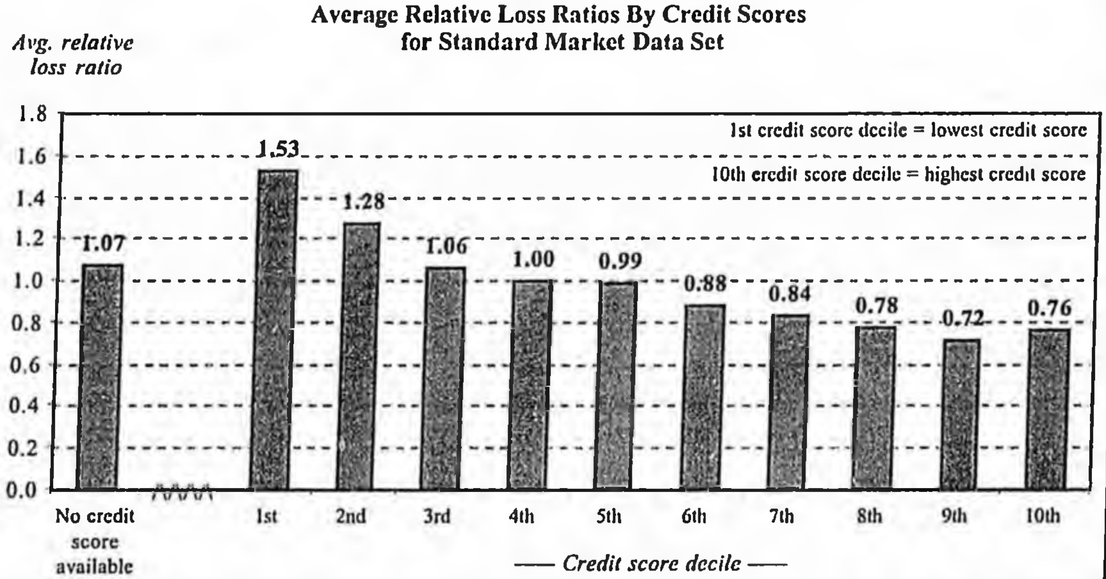
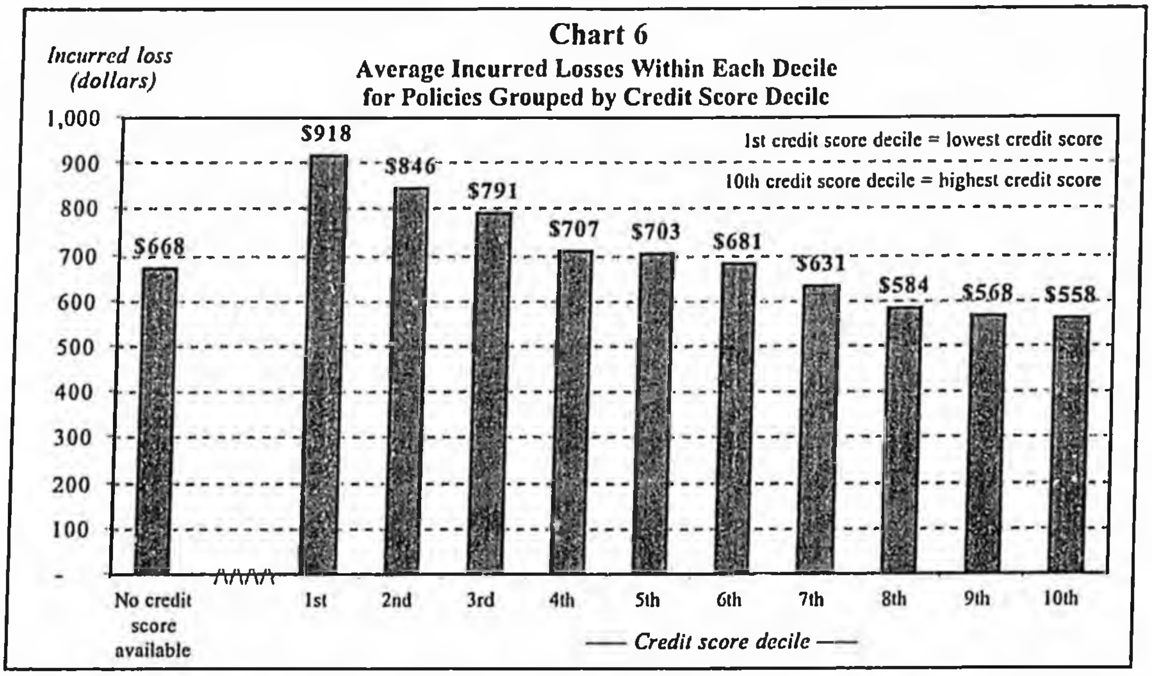
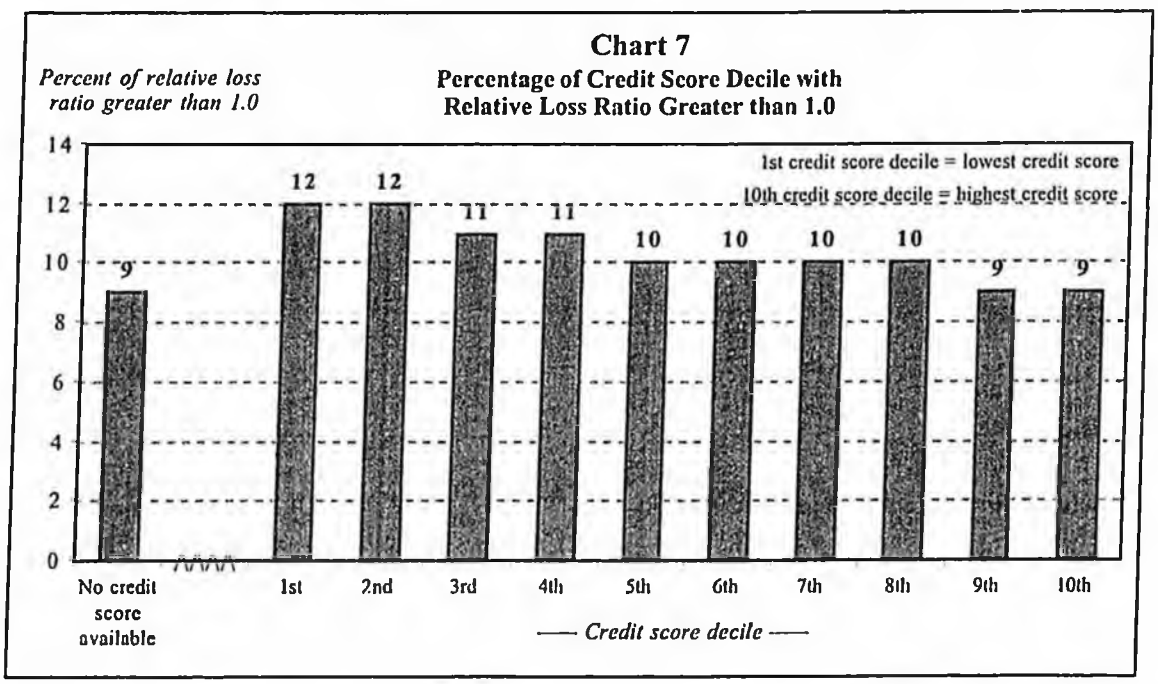


Chart 6 shows the average incurred dollar loss for each policy in each decile. Over the entire data set, the average loss per policy was \$695, but for those policies in the lowest 10 percent of credit scores, this average loss was \$918, whereas within the highest credit score decile, the average loss per policy was \$558. Thus, the average loss per policy is higher for the lowest credit score deciles and lower for the higher credit score deciles.[11]

[11] The dollar losses shown for each decile are incurred losses for the policies and do not consider premiums. The extent to which each decile group is profitable or not for the insurance company depends upon the company being able to charge premiums that exceed these losses plus other expenses. Also, while Chart 6 shows the average incurred loss for named insureds whose credit scores fall into the decile listed, it does not address the issue of whether existing underwriting characteristics account for this variability. This was accounted for in Chart 5.



Another way of showing that policies belonging to named insureds with lower credit scores have a higher probability of incurring losses is to look at the distribution of relative loss ratios in each credit score decile in the sample. Chart 7 shows the percentage of policies within each credit score decile with a relative loss ratio greater than 1.0. As can be seen, named insureds in the lowest two credit deciles are about 33 percent more likely to have a relative loss ratio greater than 1.0 than are those with credit scores in the top two deciles (12/09=1.33). A relative loss ratio of 1.0, as described in the Methodology section (above), is the target toward which individual insurers aim for specific classes of insured drivers.



Limitations of the Study

While this study found that poor credit history strongly relates to insurance losses in the automobile insurance industry, it was not designed to, nor does it, answer a number of important public policy questions. Certain critics argue that credit information collected by the three main credit bureaus (TransUnion, Experian, and Equifax) can contain inaccurate information on consumers and their credit histories, which would then compromise any subsequent credit score created by third-party commercial firms like Choicepoint for use in the insurance industry, not to mention credit scores created by insurance companies themselves. In the present study, if the credit information provided to Choicepoint for the random sample of policies contains inaccuracies, then the credit scores generated for the named insureds will be inaccurate, as well. It was beyond the scope of this study to examine the accuracy of the credit report supplied, but this certainly is important if wide-scale adoption of credit history in underwriting is undertaken.

An important proviso regarding inferences that can be drawn from this study concerns the credit score itself. The analysis in the study used the credit score created by Choicepoint. Individual insurance companies can (and do) use individual credit histories and variables contained therein to create their own credit score models and credit score values for use in underwriting. To the extent that individual insurance companies create a "better" (more predictive) credit score, the relationship found in this study may be weaker than that observed by such insurance companies. Conversely, to the extent that insurance companies use credit histories and less predictive credit scoring models than that furnished by Choicepoint, the relationship found in this study may be stronger than that observed by such insurers. To the extent that individual insurers use different formulas, results presented here should be viewed as illustrative of the relationship that can be determined between credit scoring and losses. Without access to individual insurance companies' proprietary credit scoring models, the findings presented here can only suggest the potential for a correlation between credit score and losses. This analysis is based on the Choicepoint model and cannot predict the relationship that would be exhibited by individual insurers' credit scoring models.

Another factor that should be pointed out relates to the use of credit scoring in policies having multiple drivers. As is the general practice in the insurance industry, the credit score generated by Choicepoint, which was used in the analysis presented, was based on a credit match with the identifying characteristics of the named insured (e.g., the social security number of the named insured). For multiple driver policies, each driver might have a different credit score and different incurred losses, and yet their individual losses are aggregated and associated solely with the credit score of the named insured. Consequently, it is possible for a named insured (a father, for example) to have a very good credit history, while the young son driving on the policy has a bad driving record with many incurred losses. In such a case, a "good" credit score would be associated with a policy having high incurred losses. In this regard, the current study should be interpreted as showing a significant relationship between the credit score of the named insured and losses for everyone on the policy and not as showing a relationship between the credit score of an individual driver and the losses of that particular driver. The fact that there was a significant relationship found in this study even using "noisy data" indicates that perhaps an even stronger relationship would occur if every driver's credit and record were examined separately. This was not possible in this study, nor is it insurance industry practice.

A common criticism of credit scoring and its use in underwriting decisions is that it may discriminate against low-income and/or minority applicants, and that its use, in effect, amounts to "red lining." Some within the insurance industry have maintained that their underwriting and rate-making practices are blind with regard to ethnicity and income. The database used in this study did not contain information on named insured income, ethnicity, or physical address (other than rather gross delineation of rating territory for some but not all insurers), so the results of this study cannot and do not address this issue.

Conclusion

This study analyzed a large random and representative sample of automobile insurance policies from the Texas market to determine if: 1) credit history and losses were statistically related and 2) whether such a relationship, if it exists, is explained by standard underwriting variables. The analysis found that incurred losses on individual policies are statistically significantly related to the credit score of policy's named insured (see Chart 6). Additionally, incorporating underwriting variables used by the companies through the use of relative loss ratios, it was found that there was still a statistically significant relationship between credit score and the relative loss ratio for policies (Charts 4, 5), so standard underwriting variables do not explain the observed statistically significant relationship between credit scores and losses. (The correlation between credit score and relative loss ratio is .95, which is extremely high and statistically significant.) The lower a named insured's credit score, the higher the probability that the insured will incur losses on an automobile insurance policy, and the higher the expected loss on the policy.

The Impact of Personal Credit History on Loss Performance in Personal Lines

James E. Monaghan, ACAS, MAAA

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 he 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	Group A LR	Group B Prem	Group B LR	Group C Prem	Group C LR	Group D Prem	Group D LR	All Groups Prem	All Groups 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	A LR	B Prem	B LR	C Prem	C LR	D Prem	D LR	Total Prem	Total 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 Count	Age of Driver 1 ⇒ 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 Trade Line	Age of Driver 1 ⇒ 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:

Exposure Distribution		Group			
State	Type	A	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 1 any	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	1.05	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.

Credit Profile Group	Direct Bill Earned Premium	Loss Ratio	Relative Loss Ratio	Mortgagee Bill 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.

Credit Profile Group	Urban Earned Premium	Urban Relative Loss Ratio	Suburban Earned Premium	Suburban Relative Loss Ratio	Rural Earned Premium	Rural 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

I. 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.

AMERICAN ACADEMY *of* ACTUARIES

THE USE OF CREDIT HISTORY FOR PERSONAL LINES OF INSURANCE: REPORT TO THE NATIONAL ASSOCIATION OF INSURANCE COMMISSIONERS

American Academy of Actuaries
Risk Classification Subcommittee of the Property/Casualty Products, Pricing, and Market Committee

November 15, 2002

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Purpose

The American Academy of Actuaries is the public policy organization for actuaries practicing in all specialties within the United States. A major purpose of the Academy is to act as the public information organization for the profession. The Academy is non-partisan and assists the public policy process through the presentation of clear and objective actuarial analysis. The Academy regularly prepares testimony for Congress, provides information to federal elected officials, comments on proposed federal regulations, and works closely with state officials on issues related to insurance. The Academy also develops and upholds actuarial standards of conduct, qualification and practice, and the Code of Professional Conduct for all actuaries practicing in the United States.

The Risk Classification Subcommittee of the Academy is charged with assisting legislators, regulators, and other interested parties in evaluating actuarial practices related to the affordability and availability of insurance in urban areas and risk classification issues in general.

The Credit Scoring Working Group of the Market Regulation & Consumer Affairs (D) Committee of the National Association of Insurance Commissioners (NAIC) requested that the Risk Classification Subcommittee provide assistance to the Credit Scoring Working Group. Specifically, the Risk Classification Subcommittee was asked to provide the following support.

1. Review and critique four papers that have been published in regard to the use of credit history for rating and underwriting personal lines of insurance. These four papers are:
   - The Impact of Personal Insurance Credit History on Loss Performance in Personal Lines by James E. Monaghan (2000);

- <u>Insurance Scoring in Personal Automobile Insurance - Breaking the Silence</u> by Conning & Company (2001);
- <u>Predictiveness of Credit History for Insurance Loss Ratio Relativities</u> by Fair, Isaac (1999); and
- <u>Use of Credit Reports in Underwriting</u> by the Commonwealth of Virginia, State Corporation Commission, Bureau of Insurance (1999).

2. Provide guidelines/parameters on how the NAIC could conduct a study of credit scoring, including suggestions on how the NAIC could determine (by study) causality (the relationship between credit history and risk of loss) and whether insurance scoring disproportionately affects protected classes and whether it disproportionately affects low-income groups.

3. Provide "best practices" that states could use in reviewing rating plans that use credit history in combination with other rating factors, for states that have prior approval rating laws.

This report provides our findings regarding items 1 and 3, and provides our initial advice and guidance in regard to item 2.

The subcommittee was not asked to evaluate the effectiveness of credit history as a tool in the underwriting and rating of personal lines of insurance, and therefore such an evaluation is not an element of this report. However, the subcommittee believes that credit history can be used effectively to differentiate between groups of policyholders and therefore it is an effective tool. This recognition is based on review of the four papers listed above, especially the Monaghan paper, and on the subcommittee's members' personal knowledge as obtained through the development and/or review of rating models based on credit history.

Review of Four Papers

Each of the four papers is reviewed. We first identify the major points and conclusions that are made in each paper, then review and discuss these major points and conclusions, and then provide an overall summary of the study.

Summarizing these papers very briefly:

- The Monaghan paper, written by an insurance company actuary, provides an analysis of the effectiveness of using credit characteristics to predict future loss ratios for private passenger automobile and homeowners insurance.
- The Conning & Company paper provides a disinterested overview of the use of credit history by personal lines insurers, based on review of the available literature and discussion with various parties.
- The Fair, Isaac paper, by a prominent provider of insurance scoring models, is a comprehensive response to issues that have been raised by insurance regulators and others in regard to the use of credit history.
- The Virginia Bureau of Insurance paper is a regulator's survey and discussion of the use of credit history in one state.

November 15, 2002

The Impact of Personal Credit History on Loss Performance in Personal Lines

James E. Monaghan; 2000

Study's Major Points and Conclusions

1. Eight credit information variables are identified which 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 they maintain and operate a car.
- Moral Hazard: How responsibly one manages financial credit might also correspond to how they maintain and operate a car.
- 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 likely 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 is extended to include an analysis of credit history versus homeowners insurance loss ratios, with similar results.

5. Whether or not credit information should be used. There are issues to consider other than loss performance.

- Questions remain about whether credit information should be applied to renewals, and if so, how often should it 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, so 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 the named insured, one person. 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 are in the "best" group, as regards 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 provides a comparison of urban and non-urban territories that 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.

Summary Review of Paper

The Monaghan study has the following strengths and weaknesses.

Strengths

- The study uses loss ratio and multivariate analysis to demonstrate that the credit characteristics are adding predictive power, above and beyond the existing variables.
- The study provides a good discussion of causality and how it relates to actuarial standards.
- The study addresses public policy issues that are important to the acceptance of the use of credit history, beyond causality.

Weaknesses

- The database does not allow for the analysis of renewal business.
- The database is confined to the experience of one insurance company from 1993 through 1995.

- The study was intended for a wide audiences, and therefore does not provide in-depth analytical detail. The multivariate analysis presented in the study is bivariate (two variables) and does not evaluate the importance of credit characteristics versus a combination of other rating variables.
- Many of the study conclusions are stated without providing the results of the underlying analysis. For example, tables are provided to demonstrate that credit characteristics do not appear to have a disparate impact by age of driver or by type of rating territory and then the statement is made that this also holds true for many other underwriting characteristics.

Insurance Scoring in Personal Automobile Insurance—Breaking the Silence

Conning & Company; 2001

Study's Major Points and Conclusions

1. In their underwriting and pricing process insurers seek to charge rates that are equitable, adequate and not unfairly discriminatory. These objectives are sometimes difficult to achieve because of regulatory constraints and insurers' own desires not to discriminate unfairly or act in a manner that is inconsistent with socially acceptable standards.

   From the company perspective, pricing equity and accurate cost projections are crucial. Credit data can be used to create scores that in fact provide additional predictive information about future losses. However, using credit history is often perceived to be in conflict with what society considers as fair, particularly if the individual's score is affected by catastrophic events such as divorce, medical problems or loss of a job.

2. The use of credit data in decision-making, along with having more easily accessible and reliable data, has led to the rapid growth in automated underwriting systems that minimize subjective judgment by relying on more objective, rigorous, data-driven decision processes. Automated systems are more predictive, reliable and can improve the integrity of risk classification systems.