

Underwriting with New Data and Technology— A Credit Score Example

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Introduction

In the article, "Underwriting – A Profit Engine or Lost Opportunity – Current Challenges and Potential Solutions to an Evolving Underwriting Environment"¹ the CPCU Society Connecticut Chapter researchers pointed out that underwriters are facing a data and information technology challenge. The challenge is how to embed new and rapidly changing information into the flow of the underwriting process. An example of this challenge is how to combine credit scores together with traditional private passenger underwriting criteria in the underwriting and pricing of private passenger automobile insurance. This is perhaps the most well known example of how technology is changing underwriting and where underwriters must develop both new skills in new technology and stay in control of the use of this technology for underwriting.

The traditional underwriting criteria in private passenger automobile divides potential policy holders into different risk classes and then prices the separate classes using both information about market competition and product cost. The product cost is the average expected underwriting costs, which is determined by class of risk. Credit scores provide an additional variable for underwriters to use to form risk classes and their price. This in turn provides both expected profit for the class and helps prevent adverse selection.

While credit scores can be used to differentiate classes, the use of credit scores is not without controversy. Regulators and social critics opine that credit scores are a form of redlining and some regulators have prohibited or restricted their use. Even so, the methods and models developed for using credit scores have been successful and insurers are expanding this approach to underwriting scores and other processes that take advantage of new data and new technology. Studying the use of credit scores in underwriting is instructive for understanding technological challenges that underwriters face in creating and using new sources of data and technology.

Risk Classification

Risk Classification is the process of grouping risks with similar risk characteristics so that differences in costs may be recognized.² The cost of insurance depends on the discounted expected loss costs and distribution costs including profit and contingencies. These costs can be divided into the following categories.

- Incurred losses or the cost of claims insured.
- Unallocated and allocated loss adjustment expense or the costs directly or indirectly assignable to specific claims.

Abstract

This article is the second in a series that explores some of the challenges facing the underwriting profession. One critical challenge is that of how to embed an abundance of new data and technology into effective underwriting processes that are both efficient and flexible. One of the most striking examples of how new data analyses have changed traditional underwriting processes is the development of credit scoring as an underwriting tool. The authors in this research study first examine the basic risk classification model and its social and actuarial precepts. Then they describe how insurers came to recognize and use credit scoring as a highly predictive underwriting model beyond traditional classification underwriting. The adoption of credit scoring is not without controversy or substantial costs. However, personal auto insurers have built on this new technology-supported foundation. The authors explore why and how these insurers have developed more sophisticated underwriting decision support systems. The authors conclude that the evolution of credit scoring in personal auto underwriting is an allegory for the entire industry. It provides a concrete example of both why and how building the infrastructure and skill sets for what is generically now referred to as "business intelligence" is mission critical.

- Commissions and brokerage expenses.
- Other acquisition expenses or the expenses, other than brokerage and commissions associated with the acquisition of business.
- Taxes, licenses, and fees.
- Policyholders' dividends.
- General administration expenses.
- Underwriting profit and contingency provisions.³

To maintain equity among individuals, cost differences in risk transfer should correspond to premium differences and premium differences should correspond to costs differences.

Underwriters know, and actuarial theory assumes, that individuals differ in their expected incurred losses.⁴ Woll, for example, states that the number of accidents for an individual is a function of (1) the driving environment, (2) the amount of driving, and (3) driver characteristics.⁵

While expected incurred loss costs ("loss costs") are the major component in premium rates, they are not the only costs used in developing premium rates. One of these other costs is the cost of estimating loss cost differences between individuals. When differences can be easily detected, premium rates should differ. However, there is a limitation on determining loss cost differences between individuals. There is a law of diminishing returns at work where the incremental cost of determining small differences among individuals' driving environments, amount of driving, and driver characteristics outweighs the differences in loss costs. The difference in loss costs between individuals and cost of detecting this differences can be offsetting, making it appropriate that individuals with small difference in loss costs be grouped together within the same rating class.

Traditional Risk Classification

The traditional method for reducing the cost of underwriting assessment is risk classification. Risk classification allows insurance companies to use readily available information about individuals to sort these individual risks into homogeneous classes. Common information about individuals used to define classes are: the age of the driver, sex, marital status, use, driver training, and garaging territory. Using this approach, partial information, information easily and inexpensively obtained, is used to group individuals into relatively homogeneous classes of drivers. Within the class the rates are the same.

The automobile insurance market is a very competitive market. In Connecticut in 2009, 679 non-domestic and 65 domestic insurers were licensed to write property-casualty lines of business in Connecticut. While not all of these write private passenger automobile insurance, many of them do.⁶ Long term competitive pressure in the market forces insurers to price their products based on loss costs. If they do not they will experience adverse selection, i.e., they will gain policies that are underpriced and lose policies that are overpriced based on loss costs. Determining the expected loss costs has become easier and less expensive to determine as information also becomes easier and less costly to obtain. This is driving the development of more refined risk classification systems. Technology today permits insurers to access most, if not all, rating information within nanoseconds and at an ever decreasing cost.

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The Economic Utility of Risk Classification

Risk classification in private passenger automobile insurance has been a hotly debated subject for the past several decades.⁷ Notable studies and controversies include the New Jersey Insurance Department hearing and the SRI study of risk classification.⁸ While a number of states have restricted certain types of information that can be used by insurers (such as age, sex, marital status, and territory) and have set limits on discretionary underwriting, most states let market forces determine the allocation of the cost of risk through risk classification schemes and associated insurance prices. A reason for this is that the pooling of losses in private insurance markets allows risk adverse individuals and businesses to achieve valuable reductions in risk.

The main economic argument against risk classification involves “efficiency” and “fairness.” However, most attempts to restrict risk classification have failed because the indirect costs of restrictions can be very high. These restrictions on classification undermine the private insurance market by promoting artificially conservative underwriting requirements and/or increasing the population of involuntary insurance mechanisms. Taken to its extreme, there is the fear that loss of the private insurance market would lead to government-sponsored insurance with reduced political pressure for cost control.

One main argument in the past against risk classification is that the information required is too costly. However, in the case of credit scoring as in other “new” information, the very fact that information can be gathered, stored, analyzed and retrieved by computers means the cost of relevant information has been greatly reduced. To the extent that credit scoring provides better information on expected loss costs, insurers can better allocate these costs. To the extent the total cost of risk assessment decreases, the sum of the benefits to those whose cost of risk is lower outweighs the sum of the costs to those who pay more.⁹ Thus, if credit scoring leads to better underwriting assessment and if the information can be acquired inexpensively, then it makes the insurance market more efficient.

Besides making the insurance market more efficient, higher costs can reduce the amounts of risky activities insureds undertake and their level of loss reduction activities. For example, youthful drivers, as a group, have accidents more often than older drivers. These drivers (or their parents) may delay the time they take to change from occasional drivers to principal drivers based on the cost of insurance. Other examples can be developed based on the expected accident costs and deciding whether to drive, the type of vehicle and amount of insurance to buy, and how much care to exercise while driving, etc. Restrictions on market classification distort these incentives and increase the cost of risk.

Arguments for restrictions on risk classification that are not tied to “efficiency” involve “fairness.” Automobile insurance is said to be “essential” and private insurance rates are sometimes said to be unaffordable, not related causally to losses, not within the buyer’s control, or are socially inadmissible. However, to be effective, restrictions on rate classification require regulatory constraints on insurer behavior. These constraints have costs of their own. States with comprehensive restrictions in rates and rate classification are the ones with the largest involuntary markets. They have a concentration of the urban market in the assigned risk plan. Insurers have less incentive to provide quality coverage to these involuntary market participants. Also, administrative problems arise if insurers assigned to handle involuntary market participants do not have marketing outlets or claims facilities near these participants.

Standards For Risk Classification

The primary standards for actuaries reviewing a risk classification system are *Actuarial Standard of Practice No. 12*,¹⁰ *Risk Classification Statement of Principles*¹¹, and *Statement of*

*Principles Regarding Property and Casualty Insurance Ratemating.*¹² For actuaries, pricing risk transfer is based on the estimated discounted expected value of claim costs plus a loading for distribution costs (including the costs of bearing risks). Risk classification is one of the fundamental methods for pricing risk transfer, and has been part of actuarial practice since the beginning of the profession. The need for formal standards developed as risk classification became more complex and more subject to public scrutiny.

The primary obligation in most jurisdictions is that risk classification systems be fair and equitable. To the insurance practitioner, this means the risk classification system should appropriately reflect differences in the costs of identifiable risk characteristics. A risk classification system reflects such differences by achieving the most homogeneous rate classes possible given imperfect and costly information.

A risk classification system defines a homogeneous rate class when there are no clearly identifiable subsets of the class with different expected losses. This criterion is a dynamic one that includes the possibility that new data, methods and procedures will change over time and that a more homogenous risk classification system will emerge. Credit scoring is an example of new information emerging with new techniques of risk classification based on this information.

According to Actuarial Standard of Practice No. 12, there are three primary purposes of risk classification (1) to be fair, (2) to permit economic incentives to operate, and (3) to protect the soundness of the financial security system. In order to achieve these purposes, certain basic principles should be present in any sound risk classification system:

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

The primary means of identifying costs differences among drivers with different characteristics is to show that when these characteristics are present, loss experience is different. While loss experience in statistical form is valuable as evidence, it is not the only means of identifying differences in costs. In the absence of loss experience, the underwriter may rely on expert opinion, clinical studies, and sometimes inferences without specific demonstration. If a cause-and-effect relationship can be established, then inferences without actual loss experience are particularly useful for projecting future costs. 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.

At times, “causality” is used to mean something other than a rigorous sense of cause-and-effect. It can be used for inferring the existence of a plausible relationship between the characteristics of a class and the hazard for which financial security is provided. For example, being “financially responsible” does not imply one is a “responsible” driver with lower accident potential, but it is a plausible inference and one that can be validated with actual loss experience.

Besides producing homogenous classes of risk, risk classification systems should possess certain other operational underwriting characteristics. They should contain verifiable facts that are not easily manipulated to differentiate risks. The expense of administering a risk classification system should be cost-effective. A risk classification system should prevent anti-selection or minimize its impact. Also, risk classification systems must comply with insurance laws and regulations.

Credit Scoring: an Extension of Risk Classification

As Woll points out, the expected number of accidents depends on the driving environment, amount of driving and the driver's characteristics.¹³ The traditional risk assessment systems attempt only a limited assessment of an individual's loss potential.¹⁴ The primary job of assessment systems is to sort drivers into groups having similar environment, amount of driving and driver characteristics. What information these systems use depends on how statistically valid the information is and on the resulting classes. A limitation on gathering and evaluating risk assessment information is the expense of this analysis.

One of a driver's characteristics that underwriters have always considered important is the driver's "responsibility." Do they obey the law? Do they speed or weave in and out of traffic? Do they ignore traffic signals and the safety of other drivers? Some information of this nature is in Motor Vehicle Records, but much of it is episodic information coming informally to the attention of underwriters. At one time this behavioral information has been outside the formal risk assessment system.

Credit scoring is a new way to measure an individual's "responsibility." One area that can be measured and measured inexpensively is an individual's "financial responsibility." People who are careless in their use of credit are most likely financially irresponsible. A person borrows money consciously, and in doing so they incur an obligation to their creditor. A person who consistently fails to meet their obligations is financially irresponsible. This does not mean occasional disagreements or lapses are a sign of financial irresponsibility, however, a pattern of using credit and not meeting credit obligations is a sign of financial irresponsibility. Credit scoring considers financial responsibility as evidence of an individual's responsibility generally. Statistical evidence does show that people with good financial responsibility have lower loss ratios.

Methods for Calibrating Credit Scoring Models

Credit score models and other insurance pricing models quantify the financial risks born by insurance systems. These models have two kinds of risk, process risk and parameter risk. Process risk involves risks inherent in any process involving fortuitous events. Parameter risk is the risk that the model itself is incorrect or badly specified. For risk classification systems, the traditional method for specifying the parameters is Bailey's Minimum Bias method including its modern variants using Regression Analysis. Hypothesis tests, such as the use of P-values, can be used to test model validity.

Bailey's Minimum Bias

The traditional actuarial technique for determining risk classification rate differences or relativities is Minimum Bias. It derives from two classic articles on automobile ratemaking, "Insurance Rates with Minimum Bias" by Robert Bailey, and "Two Studies in Automobile Insurance Ratemaking" by Robert Bailey and LeRoy J. Simon.¹⁵ The Bailey and Simon paper described four criteria for an acceptable set of classification relativities:

- It should reproduce the experience for each class, and overall experience, i.e., be balanced for each class and in total.
- It should reflect the relative credibility of the various groups involved.
- It should provide a minimal amount of departure from the raw data for the maximum number of people.
- It should produce a rate for each subgroup of risks which is close enough to the experience so that the differences could be reasonably caused by chance.

The classic procedures developed by Bailey¹⁶ are still in use today. For example, the 202 Class Plan from the Insurance Services Office¹⁷ is one developed using Bailey's procedure.

Linear Regression

Regression is a statistical technique used to test the strength of the relationship between two or more variables.¹⁸ Traditionally, actuaries did not use regression because they had developed their own techniques and because regression techniques require software and computer power that were not readily available. Today, with faster and more powerful desk top computers and with standard software programs such as GLIM and SAS, regression techniques are becoming more prevalent in actuarial work.

In a bivariate regression equation there is an independent "cause" labeled X and a dependent "effect" labeled Y. Bivariate regression assumes a linear relationship between X and Y as follows:

$$Y = A + BX + e$$

Where e is the error term.

The assumption of linearity and the specification of A (the "constant") and B (the "slope") can be tested using standard statistical techniques. Commercially available statistical software packages provide these tests with each evaluation of historical data. The primary method is the method of least squares, a mathematically contrived technique to produce the smallest error between the actual Ys and those predicted by the equation.

Multiple regression incorporates more than one variable as the "causes." The general equation for multiple regression is:

$$Y = a_0 + b_1 X_1 + b_2 X_2 + \dots + b_k X_k + e$$

It is in this format that regression is most often seen in actuarial work. Again, the strength of the parameters and the overall relationship between the "causes" and "effects" can be tested using standard statistical techniques. Some of the more important statistical testing techniques include a test of explanatory power (R^2), tests of significance of the parameters (standard errors), and tests of the specification (hypothesis tests and tests of residuals).

Generalized Linear Regression Models

A more modern version of Bailey and Simon's procedure was developed by Robert L. Brown¹⁹ and further discussed in Zehnwirth.²⁰ In his paper, Brown shows that Bailey's multiplicative model is equivalent to a statistical approach using general linear interactive modeling.²¹ Insurers' credit scoring systems have been developed using regression techniques as described in Brown's paper on minimum bias. Using modern statistical software packages, actuaries and statisticians can model and test the relationship of credit scores to loss ratios.

An Example of a Credit Scoring Model

An example of a scoring model starts with credit information from a credit reporting agency, such as Trans Union. Trans Union, like other credit reporting agencies, gathers data on credit users and sells this information to insurers in machine-readable credit reports. Insurers, or their vendors, such as FICO (formerly Fair Isaac), then develop statistical credit scoring models using credit reporting agency data and the insurers loss data from the insurers own policy holders. The object of the exercise is to build systems that can price applicants at the point of sale using credit scores and traditional underwriting criteria.

Credit reporting agency information is credit-related and does not contain all information on a person's life. The following is a list of the general categories of information on credit report data:

- The inquirer's name and identification information.
- The consumer's name and identification information.
- Model score—Trans Union has its own proprietary scoring models used to predict such things as the chance a consumer will become delinquent (Empirica), bankrupt (New Delphi), or have a certain expected loss ratio (ASSIST).
- Credit summary—A snapshot of all activity on a consumer's credit report.
- Public record—This field provides information on such events as civil judgments, bankruptcies, and tax liens.
- Collections—Information about consumer accounts transferred to a professional debt-collecting agency.
- Detailed credit and payment information—The consumer's historical and current account record with different creditors are shown. The information includes the type of credit, amounts of credit, payments and other related information such as the time the account was open or closed, the manner of payment, delinquency, and so forth.
- Inquiries—Trans Union's credit report maintains a record of creditors who have requested an individual's credit history in the previous two years.

A credit report agency calculates hundreds of standard credit characteristics from these general categories. These standard characteristics include such things as "number of accounts opened in the last twelve months" and "number of accounts with past due balances." The insurer or its modeling agency then develops a proprietary scoring model starting from these standard characteristics together with the loss experience of perhaps millions of policies in force.

The approach an insurer can take in specifying its credit scoring model is to use linear regression as described above. It first calculates correlations between each pair of the credit variables. Many of these variables are correlated, and including all variables may produce spurious results. Using the statistical correlations among the credit characteristics, and from their explanatory powers,²² the insurer can often pare the number of variables down to ten. Using loss ratios and/or loss costs²³ as the dependent variable, the insurer can then develop multilinear regression equations among the ten variables and the dependent variable.

It is reasonable to assume the meaning of credit, as it relates to personal characteristics, varies within traditional underwriting characteristics such as the age of the driver. If so, then a more accurate predictor of losses may be one that uses different regression equations that include credit scores within traditional categories of characteristics. Thus the insurer may have separate regression equations for three different categories of age—youthful drivers, middle-age drivers, and older drivers. This would be an underwriting decision. Any model regression should be judged on whether it shows a strong linear relationship between credit score and both loss ratios and loss costs.

Credit Scores With Traditional Rating Variables

Using credit scores in a risk classification system is like standard underwriting assessment systems in that they do not attempt to detect an individual's direct risk of

loss. Instead, they use ancillary information to sort individuals into pools of insureds with equal—or at least similar—risk characteristics. As noted in the NAIC’s White Paper,²⁴ some regulators are skeptical of the use of the loss ratio method to establish a correlation between credit history and loss experience for a variety of reasons. These regulators believe the relationship may be spurious. The example given is the relationship between gray hair and income. For insurers, however, causality means a plausible relationship can be established. They believe an individual’s direct risk of loss depends on the driving environment, the amount of driving, and the driver’s characteristics. Any ancillary information that can be reasonably linked to these three factors is causally linked to the risk of loss.

Among the traditional driver characteristics cited in the literature that determine an individual’s risk of loss are:

- Driver’s age, occupation, location of residence, citizenship, and marital status.
- Personal traits, such as drinking habits, job and residence stability, morals, credit rating, previous insurance, criminal records, past claims activity, and personal knowledge of the agent to the insured.
- Driving ability and driving record, health problems, familiarity with the driving area, and date of first issue or license.²⁵

Many of these traditional driver characteristics are behavior characteristics. Because financial responsibility is a behavior characteristic, it is hardly surprising that it is an indication of a driver’s characteristics and can be included in the list of ancillary information about driver characteristics.

Validating the Use of Credit Scores

Once a characteristic such as credit scoring is chosen for risk assessment, the proof of its validity is in the statistical evidence. By their very nature, insurance statistics cannot determine who will have accidents, only how many accidents will occur and how costly those accidents will be for pools of insureds. The relationship between a particular characteristic and loss costs is in the statistical evidence. In the case of credit scoring, it is in the strength of the correlation as shown by regression analysis.

One powerful figure for showing statistical evidence is the R^2 statistic. This statistic measures the amount of the total variation in loss ratios (or loss cost) that is removed or “explained” by the credit score. If, for example, the R^2 statistic for a particular model was measured at 0.800, then this means that 80.0 percent of the variation in loss ratios for pools of insureds can be removed by associating loss ratios with credit scores. This level of explanatory power is very high.

Another statistic is the t -statistic for constants, such as A and B in the following equation:

$$\textbf{Loss ratio} = \mathbf{A} + \mathbf{B} \text{ (Credit variable)}$$

The t -statistic measures the probability that a constant is significantly different from zero. If it is zero, then the constant and the variable it is joined with should be removed as a term of the equation.

A third test for underwriting variables in regression equation is the P-value²⁶ of the regression. The P-value tells the modeler how strict a level of evidence one would require before he or she should conclude the regression equation does not fit the data. If the P-value is at or near zero, then this means, in terms of the statistical test, that there is no level of statistical evidence that would cause one to reject the linear hypothesis.

Multiple other statistical models test the validity of computerized underwriting routines. Underwriters don't have to carry out the tests, but they do need to judge how underwriting decisions are made using these models. They must understand the meaning and results of these statistical tests in order to evaluate how these models are working.

Underwriting Decision Support Systems

An understanding of underwriting decision support systems requires a discussion of the framework for marketing and underwriting private passenger automobile insurance. Today, direct writers share about 50 percent of this \$170 billion marketplace with agency companies. Many direct writers and those with exclusive agents provide prospective consumers access to their program through aggregators such as www.insurance.com or www.onlineautoinsurance.com. Agency companies provide access through the agents that represent their company. These auto insurers most likely have provided both the aggregators and agents with defined underwriting characteristics that they are willing to consider. This initial screening takes place beyond the view of the consumer.

Once an applicant makes it through to the company's proprietary underwriting and pricing system, he or she will then be required to submit application information. The insurer (and/or agent) will, in the background, obtain MVR, CLUE, and credit/underwriting score information. The insurer's underwriting, actuarial, and marketing departments will have created an underwriting and pricing system that processes all of this information through highly sophisticated formulas and algorithms to produce an acceptance or rejection and, if an acceptance, the price for the class into which this applicant falls.

Insurers are moving to multiple-tier pricing programs that cover a very wide range of acceptable insureds, up to and perhaps including drivers who would otherwise qualify for the involuntary market. The aim here is to offer a price to all applicants. The price, however, may not be competitive for certain classes, as they may fall outside the insurer's underwriting criteria. As an example, a driver who either is or should be in the assigned risk pool may be quoted a price that is higher than that of the pool.

Historically, auto insurers have relied on traditional rating factors, such as age, vehicle use, garaging location, gender, accidents and violations, and so forth. Today auto carriers are using rating plans that include elements that serve as proxies for actual loss experience, including credit score, occupation, education, and more cars than drivers. It is here that the underwriters and actuaries blend underwriting criteria and pricing based on traditional factors and these additional proxies for loss experience.

So where do underwriters fit into this automated system? They do, or should, function as a "court of appeal" for the sales department of a direct writer or an agent of an agency company. While the underwriting support system will continuously and consistently apply the company's underwriting criteria, it cannot treat the exceptions to the rule. For instance, a single female architect may have a poor credit score as a result of her ex-husband's credit history. She is recently divorced and is in the process of establishing her own spotless credit history. This situation will no doubt be referred to an underwriter for consideration. Or take the case of a single female with two cars. The underwriting system may up-rate (or decline) this prospect until an underwriter can confirm the use of the other vehicle. This analysis may uncover a boyfriend in the household, or it may find that the applicant uses the older vehicle to commute to the railroad station and has another car that she uses on weekends.

The private passenger underwriter is, or should become, a book of business manager. He or she should be in a position to do at least these tasks:

- Monitor and report on the underwriting results for his or her assigned segment of the book.
- Track the exceptions that are made and their historical results.
- Monitor the accuracy of the formulas or algorithms used to select and price the business.
- Suggest new elements in formulas or algorithms to be tested statistically.
- Conduct audits of his or her book segments.
- Support the sales and marketing departments through interdepartmental meetings and ongoing training programs.

Conclusion

New data gathered with information technology can be used with underwriting expertise to develop and administer an insurer's management of underwriting plans and execution. The use of credit scores in underwriting over the past two decades is an example of how new data and information technology can be wed to traditional underwriting methods. Reliable actuarial and statistical evidence exists that there is a strong relationship between credit scores and the cost of insurance, and that credit scores are not proxies for other rating variables. As insurers find additional proxies for loss experience, these insurers will continue building confidence that they can support and augment their underwriting decisions using statistical methods and computer collected empirical data. As long as insurers incorporate credit scores with other easily obtained rating variables in balanced underwriting/pricing systems, automation of the underwriting and pricing of private passenger auto insurance can become the rule rather than the exception. This development will then elevate the underwriter to higher levels in the organization's decision-making hierarchy.

These developments in the pricing and underwriting of personal auto serve as a model for the industry and a springboard for the expansion of this approach to other lines of business. While it is true that rating and underwriting data elements may not be as easily or as inexpensively obtained for commercial lines as they are in personal auto, the methodology for collecting information from various sources and processing it as business intelligence should enable all underwriters to make consistent underwriting and pricing decisions. It could also cause the demise of an oft-quoted line that goes something like, "Running an insurance company is like running a supermarket where the price of the product is determined by the checkout clerk."²⁷

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3. Casualty Actuarial Society, *Statement of Principles Regarding Property and Casualty Insurance Ratemaking*, May 24, 1988, pp. 73-74,
4. A common assumption is that individuals have a frequency of loss best described by a Poisson or Negative Binomial probability distribution and a severity of loss best described by a skewed probability distribution such as a Lognormal. Convolved together, these two form a Compound Poisson Distribution.
5. Woll, *A Study in Risk Assessment*, Proceedings of the Casualty Actuarial Society, Vol. LXVI, pp. 84-138.
6. State of Connecticut, "The One Hundred Thirty Ninth Annual Report of the the Insurance Commissioner 2010," Table 2.
7. See Forgue, Raymond E., Consumer Opinions of Automobile Insurance Classification, Pricing Practices and Proposed Reforms, *Journal of Insurance Regulation*, Vol 1, No. 3, (1983).
8. See New Jersey Department of Insurance Hearing on Automobile Insurance and Related Methodologies: Final Determination — *Analysis and Report* (1981) and *Stamford Research Institute, The Role of Risk Classification in Property and Casualty Insurance* (1976). Discussion of these and other risk classification matters can be found in *The Insurance Classification Controversy*, by Regina Austin, University of Pennsylvania Law Review. Vol. 131, No. 3.
9. Harrington and Doerphinghouse, op cited, identify this efficiency as Pareto efficiency.
10. Actuarial Standards Board, *Actuarial Standard of Practice No. 12: Concerning Risk Classification*, October 1989.
11. American Academy of Actuaries, Committee on Risk Classification, *Risk Classification Statement of Principles*, June 1980.
12. Casualty Actuarial Society, *Statement of Principles Regarding Property and Casualty Insurance Ratemaking*, May 1988.
13. See Woll, *supra* note 4.
14. Merit rating systems, such as the Safe Driver Incentive Plan (SDIP,) do use individual records of accidents and convictions to partially rate individuals. However, these rating systems provide only limited information about an individual's potential for future accidents.
15. Bailey, R. A and Simon, L.J., "Two Studies in Automobile Insurance Ratemaking," PCAS Vol. XLVII, page 1 and Bailey, R. A. *Insurance Rates with Minimum Bias*, PCAS Vol. L, page 4.
16. One of the more popular models with actuaries is the so called multiplicative model. As an example, suppose rates were base two parameters, say class and driving record. If we let $r(i,j)$ be the average loss costs for $n(i,j)$ risks that can be have characteristic $x(i)$ and $y(j)$. Bailey's model set $x(i)$ as follows:
$$x(i) = \frac{\sum n(i,j) r(i,j)}{\sum n(i,j)}$$

and similarly for $y(j)$

$$y(j) = \frac{\sum n(i,j) r(i,j)}{\sum n(i,j)} x(i)$$
17. See, for example, ISO's Connecticut Rules Filing—PP-96-RS01, p. 16.
18. A good beginner's text on regression is Michael S. Lewis-Beck. (1980) *Applied Regression: An Introduction*, Sage University Paper Series on Quantitative Applications in the Social Sciences, 07-022. Newbury Park, CA: Sage.

19. Brown, Robert L., "Minimum Bias with Generalized Linear Models: Ratemaking Automobile," *Proceedings of the Casualty Actuarial Society*, Vol. LXXV, p. 187.
20. Zehnwirth Ben, "Ratemaking From Bailey and Simon (1960) to Generalized Linear Regression Models," *Casualty Actuarial Society Forum*, 1994 Ratemaking Call Papers, 1994.
21. Brown, *supra* note 19, shows that if you assume the incurred losses for cell (i,j) can be modeled as a Poisson density function, then maximum likelihood estimation will reproduce Bailey's multiplicative method.
22. This is done using two statistics that are known and the R² statistic and the t-statistic.
23. Loss ratios are the incurred losses divided by earned premiums. Loss costs are the losses and loss adjustment expenses divided by earned premium.
24. National Association of Insurance Commissioners, *Credit Reports and Insurance Underwriting*, December 1996.
25. Stanford Research Institute, *The Role of Risk Classification in Property and Casualty Insurance: A Study of the Risk Assessment Process*, May 1976, p.19.
26. Wayne D. Holdredge, "Fair Isaac—Insurance Bureau Scores vs. Loss Ratio Relativities," December 1996. Tillinghast measured the p-value of Fair Isaac's credit scores for several companies. They also found credit scores were a significant predictor of loss ratios.
27. Franklin (Tad) Montrose, President and Chief Underwriting Officer for General Reinsurance Corp., described the point in his May 2007 paper entitled "Underwriting Art vs. Science."