A View Inside the "Black Box:" A Review and Analysis of Personal Lines Insurance Credit Scoring Models Filed in the State of Virginia

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Abstract

In order to reveal and better understand the inner workings of insurance credit scoring models used by the vast majority of personal lines insurers, the authors obtained nine private passenger automobile and two homeowners' filings from nine insurance groups from the Virginia Bureau of Insurance. Within these filings the authors found three categories of models created by either Fair Isaac & Company, ChoicePoint, or the insurance companies providing the filings. Based on the review and aggregation of these filings, the authors will describe the data sources, scoring functions, scoring algorithms, model variables, and statistical details of these models. In addition to descriptive information, interpretive and explanatory details for the models will be included based on the authors' past experience in conducting predictive modeling projects that included both mainstream and non-traditional predictive variables as well as personal credit information. As a result, the readers will gain a better understanding of how the insurance industry utilizes credit information to formulate insurance credit scores.

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Acknowledgements

The authors would like to thank Hrisanthi "Chris" Adamopolous and Michael Brodnick for their assistance researching topics for this article. We would also like to thank the CAS Ratemaking Committee and our colleagues in the Advanced Quantitative Services (Data Mining and Predictive Modeling) practice at Deloitte & Touche for their review and critique of the form and content of this article.

I. Introductions

I.1 Credit Scoring as a Hot Topic

For nearly 15 years the personal lines P&C insurance industry has been studying and utilizing individual credit history in a variety of ways for ratemaking and underwriting activities. Over this timeframe, the industry's use of credit history as a tool has become extremely widespread to the point that as of 2001, 92% of the respondents to a Conning and Company survey use some form of credit scoring [1]. The respondents to this survey represent approximately 45% of the top 100 insurers by premium volume.

Most of these companies consider the details of the credit scoring models they use, and the methodologies with which they use them, to be proprietary and not something to be publicly disclosed or openly discussed. This "black box" image coupled with a variety of usage and implementation questions and anomalies experienced by consumers and a general concern over personal information privacy, has sparked considerable public debate about the appropriateness of insurance credit scoring [2,3].

Despite this widespread use of credit history in the insurance process, over the past few years the topic of credit scoring as a risk selection and pricing tool for private passenger automobile and homeowner's insurance has become an extremely hot legislative and regulatory topic. The topic has been at the forefront of a variety of newspaper, magazine, television, and radio coverage as well as high profile state legislative and insurance regulatory debates [2,3]. Recently, actuaries have been actively participating in the debate [4,5,6,7] as well.

Much of the concern and doubt may stem from the insurance industry's historical unwillingness to open up the credit scoring "black box" and show consumers, regulators, and industry watchers what is inside. Without a detailed understanding of what's inside the "box" and how it corresponds to insurance risk and policy pricing, allegations have emerged regarding the unfairness of credit scoring and the manner in which it is assumed to discriminate against various population subgroups.

On one side of the debate are the insurance companies and insurance trade organizations that passionately defend the use of credit scores as a valid insurance tool. They argue that the use of credit as a predictor of future insurance loss is statistically valid, objective and impartial, and does not discriminate in favor of, or against, various societal groups.

On the other side are the consumer action groups and other public advocacy organizations. Their numerous concerns include arguments that credit scores are inherently biased (even if that is not the intent of the scores), contain inaccurate information that is difficult to correct, favor one socioeconomic group over another, or do not provide scientifically valid results. They conclude by saying that the use of credit scores as an insurance risk selection and underwriting tool display correlation but not causality.

As a result of the debate and its political sensitivity, state legislators and state insurance departments have stepped up their review and scrutiny of the issue. By Spring 2003, nearly 40 states have introduced new or additional proposals, or have laws pending, for legislative and regulatory control over insurance credit scoring [8]. Furthermore, in 2002 alone, eleven states passed laws that control or limit the use of credit scoring. These laws contain language that ranges from outright prohibitions on credit scoring in specific contexts to controls around the applicability of credit scoring techniques, credit data usage, information disclosure to consumers, risk selection and pricing methodologies, underwriting action protocols, etc.

I.2 The "Black Box" Opens

One of the states focusing considerable attention on the insurance credit scoring issue was Virginia. On June 17, 2002, Alfred W. Gross, Virginia Commissioner of Insurance, issued Administrative Letter 2002-6 mandating that "all insurers licensed to write private passenger automobile insurance and homeowners' insurance in Virginia" must file credit scoring models that are used for risk rating or tiering. Furthermore, Mr. Gross stated, that all such filings would become "part of the [company's] rate filing and will be open to public inspection" according to state law. This action is an example of a recent trend that allows the public more direct scrutiny of the inner workings of insurance credit scores.

I.3 Models Available for Study and How They Are Described in this Paper

Shortly after the filing deadline and using a November 2002 Virginia Bureau of Insurance (DOI) list of forty or so companies that had filed credit scoring models with the Bureau as given in Exhibit 1, we selected and obtained copies of eleven filings, nine for private passenger automobile and two for homeowners', to be used for this study. Our methodology for selecting these models was to obtain representative samples of the different types/categories of models that are used by the population of filed companies for both private passenger automobile and homeowners' coverages.

Upon initial examination, it became readily apparent that the majority of filings utilized "industry" or "customized" models that were developed and provided by either Fair Isaac Company (Fair Isaac) or ChoicePoint. A few large national companies also filed models that were apparently developed by the filing insurers and are "proprietary" to those companies. We therefore obtained filings for companies falling in each of these three model source categories: (1) Fair Isaac; (2) ChoicePoint; and (3) Proprietary.

I.4 What this Study Is and What it is Not

As members of the insurance industry we do not feel it is essential to be too revealing in this paper. We respect the rights of insurance companies to preserve some level of confidentiality and propriety with regards to the credit scoring models that they use and how they use them. As a result we will not be attributing insurance company names to the model details that we will discuss in this paper. We will name Fair Isaac and ChoicePoint as creators of categories of models however because we believe that, as industry standard model providers and vendors of insurance bureau scores, many of the details for their models described in the filings have already been provided in public testimony, public relations descriptions, and are standard and consistent across companies utilizing them. We believe that their models represent the current majority of insurance credit score usage and as such can be openly discussed without targeting proprietary company specific information.

We intend for this paper to review the basic form and structure of insurance credit scoring models. Such information coupled with our analysis should provide additional understanding of how these models combine personal credit history and credit information to formulate a scoring process that is representative of a consumer's general financial stability, credit utilization and behavior, and a consumer's pattern of debt payment. We will not be rendering any judgments on which models are better or worse as business tools for predicting insurance claims experience or insurance policy profitability. Rather we will, as objectively as possible, examine and analyze the filings we have obtained and describe patterns, similarities, differences, strengths, and weaknesses in the structure and logic of the models.

II. Review of the Credit Scoring Models

II.1 General Information for the Reviewed Credit Scoring Models

As stipulated by the Virginia Bureau of Insurance, insurance companies need to file the details of their credit scoring models if they utilize credit scores for rating and tiering in the state. Exhibit 2 lists the eleven filings reviewed in this study, and some of the general information regarding these filings is as follows:

- The eleven filings are from nine insurance groups that were selected from the companies in Exhibit 1. The 2002 homeowners' and private passenger automobile premium written by these 9 insurance groups according to the Best data [9] are also given in Exhibit 2.

- Nine of the eleven filings are private passenger automobile filings, and the other two filings are homeowners' filings. Exhibit 1 shows that there are more credit filings for private passenger automobile than for homeowners' in Virginia, suggesting that credit scores, industry-wide, are used more often in private passenger automobile than in homeowners'. This is consistent with much of the recent industry discussion surrounding the use of credit scores and our experience.

- The models we reviewed fall into three major groups – Industry/Fair Isaac models, Industry/ChoicePoint models, and proprietary models. There are four Fair Isaac models used by three insurance groups, three models for private passenger automobile and one for homeowners'. Another four insurers use the ChoicePoint model for their private passenger automobile books of business. Finally, two insurers developed their own proprietary models. One of them uses one model for both homeowners' and private passenger automobile, while the other uses one model for their private passenger automobile business.

In the following sections, we will discuss these models in detail.

II.2 Industry - Fair Isaac Private Passenger Automobile and Homeowners' Models

Fair Isaac Inc. offers a series of models, called Fair Isaac models, to the marketplace in two primary varieties, private passenger automobile vs. homeowners', and by market segment (e.g. preferred vs. standard vs. non-standard). The models are updated by Fair Isaac on a periodic basis to reflect recent data experience and other data factors. Insurers can pick and choose which model(s) they want to use through discussions with Fair Isaac regarding the predictive power, variable characteristics, etc. for their menu of models. In general, these Fair Isaac models share fairly similar variables and scoring algorithms, and we have seen on occasion that private passenger automobile models are sometimes utilized for homeowners' policy credit scoring, or vice versa.

The following further describes the variables and the scoring algorithm of the models. Additional comments regarding the model comparison and model insight will be given in later sections:

- Data Source – the Fair Isaac models analyzed in this study are based on credit information from TransUnion.

- Variables – the Fair Isaac models use from ten to thirteen credit variables. The variables include the following categories: late payment/past due/delinquent information, derogatory information, bad debt/default/unsatisfactory information, collection information, and other variables. Variables in the last group, the "other" group, contain various pieces of account information, such as the number of accounts, history of accounts, etc., and debt/financial leverage information. Exhibits 2 and 3 compare the variables used in the Fair Isaac models with those of the other models.

- Scoring Algorithm – now that it is available for analysis, the scoring algorithm used in the Fair Isaac models is not overly complex and can be understood in a straightforward fashion. The three steps for the algorithm are:

  1. Assign an individual score for each variable.
  2. Sum the individual score across all variables to derive the total raw score.
  3. Scale the total raw score to the final calibrated score.

- Score Scaling Function - the Fair Isaac models employ a series of linear scaling functions to transform the raw score to the final score by different score ranges. For example, for the Assist 2.0 Fair Isaac model, also labeled as the Preferred Auto Min Limit model, the scaling process is as follows:

- If (raw score+244) < 625 then the final score = raw score + 244
- If (raw score+244) is between 625 and 724 then the final score = 1.2 x (raw score + 244) – 146
- If (raw score+244) >= 725 then the final score = 1.5 x (raw score + 244) – 363.

Please note that the score at the two boundaries within this algorithm (i.e. 390 and 490) is continuous.

- Score Range - the Fair Isaac models assign higher scores to better risks and lower scores to poorer risks. A typical score range is between 200 or 300 for the low end of the score range to 800 for the high end of the score range.

II.3 Industry - ChoicePoint Private Passenger Automobile Model

Unlike the Fair Isaac models, based on our examination of the Virginia filings, ChoicePoint offers the insurance credit scoring marketplace only one model for private passenger automobile and one model for homeowners'. In addition, our historical experience is that ChoicePoint tends to be more willing to provide specific model details for explanatory review and investigation by regulators, insurance companies, and consumers. We reviewed the ChoicePoint model for private passenger automobile in this study.

Compared to other credit models, the ChoicePoint model has the most number of predictive variables and has, perhaps, the most complicated scoring algorithm:

- Data Source – the model in this study uses credit information from Experian.

- Variables – the ChoicePoint model essentially contains two sub-models, one for "thin file" customers with less than four credit accounts on file and the other one for "thick file" customers with four or more credit accounts on file. The model has twenty-nine variables for the "thin file" accounts and thirty-seven variables for the "thick file" accounts. Another unique feature of the ChoicePoint model is that it employs many different types of credit accounts, such as retail accounts, finance accounts, oil and gas card accounts, automotive credit accounts, etc. In addition, ChoicePoint uses many different debt/credit leverage ratio variables, such as the ratio of outstanding balance to available credit limit on open bank revolving accounts. Further study indicates that many variables in this "other" group do not appear to have a significant contribution to the final score.

- Scoring Algorithm – the model's algorithm is perhaps the most complicated algorithm among all of the models reviewed in this study. The algorithm has five steps:

1. Determine whether an account is a "thin file" or a "thick file" account - while the algorithm and structure are the same between the two accounts, the parameters, the variables, and the score scaling functions are different.
2. Calculate ScoreCard 1- in a manner similar to the Fair Isaac algorithm, for ScoreCard 1 the model first assigns a weight to each variable and then sums the individual weight across all variables. However, unlike the Fair Isaac models that use integer scores, ChoicePoint assigns real and fractional numbers to the weights. There are sixteen variables used for the thin file ScoreCard 1 and twenty variables used for the thick file ScoreCard 1.
3. Calculate ScoreCard 2- to calculate the ScoreCard 2 value, the model assigns different weights to each variable, sums the weights across all the variables, and then takes the exponential function of the summed result. It should be noted that exponential functions are widely used for log-linear regression modeling processes, GLM, and neural networks. There are twenty variables used for the "thin file" accounts and fifteen variables used for the "thick file" accounts.
4. Calculate the raw score - the raw score is equal to the ratio of ScoreCard 1 to ScoreCard2. Since ScoreCard1 is a linear function and ScoreCard2 is an exponential function, the ratio of the two will create a unique and complex feature for the raw score. We are not certain as to what the advantages are in employing different functions for the ratio. One thing we notice is that while ScoreCard 2 uses an exponential function, many of the weights are fairly small. When such weights are small in an exponential function, the result can be approximated by a linear function. Another unique feature of the algorithm is that several variables exist in both ScoreCard 1 and ScoreCard 2. Therefore, their overall contribution will be a combination of the contributions in the numerator and in the denominator of the ratio. Due to these complexities, the algorithm is not as easily understood and the effect of each variable to the overall score is not as apparent as other models.
5. The last step is to scale the total raw score to the final calibrated score. While the weights and variables are different between the thin and the thick files, the raw scores are calibrated so that the final scores are brought to the same level between the thin and the thick file policyholders.

- Score Scaling Function – in a manner that is similar to the Fair Isaac models, the ChoicePoint model employs a series of linear scaling functions to transform the raw score to the final score by different score ranges. The model uses different scaling functions between the thin file and the thick file accounts so that the final score gets calibrated to the same level between the two.

- Score Range - as with the Fair Isaac models, the ChoicePoint model also assigns higher scores to better risks. The ChoicePoint score range is, in theory, between 200 and 998.

II.4 Company #1's Proprietary Private Passenger Automobile and Homeowners' Model

The first proprietary model reviewed in this study is applied to both homeowners' and private passenger automobile. The model algorithm and variables appear to be similar to the Fair Isaac models, but the score scaling function and the final score range are different:

- Data Source – the model uses credit information from TransUnion.

- Variables – the model has ten variables. One group of variables used in other models that are not included in this model are the bad debt, account default, and unsatisfactory account information types of variables.

- Scoring Algorithm - the algorithm has three main steps:

    1. Assign an individual score for each variable.
    2. Sum the individual score across all variables to derive the total raw score.
    3. Scale the total raw score to the final calibrated score.

- Score Scaling Function - the transformation process to scale the raw score to the final score is straightforward:

    - Final score = raw score + 100

- Score Range - unlike the industry Fair Isaac and ChoicePoint models, the model assigns higher points to poorer risks and lower points to better risks, and the score range is from 100 to 1000.

II.5 Company #2's Proprietary Private Passenger Automobile Model

The second proprietary model reviewed in this study is for private passenger automobile. The following describes the variables and scoring algorithm used in the model:

- Data Source – the model uses credit information from TransUnion.

- Variables – the model employs many variables, thirty six variables, but several of the variables are transformed in a manner whereby there are multiple timing variables for the same event and occurrence. One example is the number of the accounts open over the past 12, 18, and 24 months. Therefore, there are three variables used for the same information that are different only in the length of the experience period. Another example is the number of accounts 30 or more days past due within the past 3 months, 6 months, 12 months, 18 months, and 24 months. One group of variables not used in this model is data pertaining to collection information.

- Scoring Algorithm – the model employs a linear scoring function with a highly nonlinear score scaling function:
  - o Calculate the raw score - the raw score is calculated by a standard linear formula that combines an intercept term and a series of the products of parameters and variables.
  - o Transform the total raw score to the final calibrated point.
- Score Scaling Function – the model employs a highly non-linear function that will scale the raw score to a final score range of from 1 to 100:

$$\text{Final Score} = 100 * (1.0056 - \{[8.8533/(\text{Raw Score} + 9.0691)]^{2.3009}\})$$

  Exhibit 4 shows in a graphical format the relationship between the raw score to the final score.

- Score Range: Like the first proprietary model, this model assigns higher scores to poorer quality risk and lower scores to better quality risk. The score range is from 1 to 100.

III. Model Comparison and Additional Comments

Exhibits 2 and 3 summarize some of the model discussion points described above. We will now provide some additional comments regarding the models.

III.1 Model Variables

- In general, the credit variables used in these models can fall into six categories:
  - o Late Payment/Past Due/Delinquent information,
  - o Derogatory information,
  - o Inquiry information,
  - o Collection information,
  - o Bad Debt/Default/Unsatisfactory information, and
  - o Other (such as Debt Leverage information and Account information)
- It appears that all of the models use information for late payment, derogatory, and inquiry information. One model does not use collection variables and one another model does not use variables in the bad debt group. Variables in the last group, other group, vary the most from one model to another.
- Exhibit 5 summarizes how each of the variables impacts the risk quality predictions in these models. For most of the variables, their impacts on the risk quality are consistent among the models. For example, all of the models indicate

that higher numbers of late payments are indicative of a poorer quality risk. Few of the variables may exhibit a U-shape or an up and down (or vice versa) shape relationship with regards to the resulting score.

- The variables that differ the most from one model to another are in the "other" group. This is especially true for the ChoicePoint models and Company #2's proprietary model. Each of these models has more than 10 variables in this category. However, we notice that other than a few variables, such as the history of the account, most of the variables in this category do not seem to have a significant contribution to the final score. Perhaps, these variables are used to explain a multivariate effect when the models are applied to different books of business.

- It appears that the variables and the scoring algorithms used in the various Fair Isaac models are quite similar. Between the private passenger automobile and homeowners' models, many of the same variables are utilized. The fact that the Fair Isaac private passenger automobile and homeowners' models are similar suggests that there exist many common underlying credit characteristics between private passenger automobile and homeowners' that are correlated with private passenger automobile and homeowners' losses. Company #1's usage of the same model for both homeowners' and private passenger automobile further supports this indication. However, in order to directly compare different models when they are applied to a book of business, the scores need to be normalized. One approach to achieve such a score normalization is to use score ranking, instead of the final score. This will be explained further in section III.4.

- In order to evaluate the influence of a variable on the model, we can perform a delta method, which is a variable sensitivity test. This method is to evaluate the change in the final score by varying the value of a variable one at a time. The change in the variable values will first impact the raw score, then the final score.

  For illustration purposes, we will show in Exhibit 6 such test for two variables, the average months in the credit file of all accounts and the number of inquiries for the credit file, on three different Fair Isaac models. Exhibit 6 shows that for the Assist 2.0 – Preferred Auto Min Limits model, for example, when average months in file changes from 0-20 months to 21-23 months, the final credit score will increase by "1" for total score <625, by "1" for score between 625 and 724, and by "2" for score >=724. It is interesting to point out that for the two variables tested in Exhibit 6, how the variables impact the final credit score is the same among the three models - the higher the average months in file, the higher the score and the better the risk; the higher the number of inquriries, the lower the score and the worse the risk. Next, we perform a normalization test to compare the degree of the impacts. Due to different score ranges and scaling functions used from one model to another, we need a normalization process to have a meaningful comparison, and the result is given in Exhibit 7. In Exhibit 7, for the impacts in each column from Exhibit 6, we divide them by the first number in the column. Exhibit 7 clearly indicates that for the two variables tested here, their strengths are very similar among the three models.

Two more things need to be noted for the variable sensitivity test:

1. For a non-linear scoring formula such as the ChoicePoint approach, the result is not a constant and is dependent on the values of other variables.

2. Sometimes multiple variables are correlated and they are not completely independent. For example, for the Company #2's proprietary model, there are three late payment variables, late payments over the past 12, 18, and 24 months. Therefore, if we increase the late payment variable from 0 to 1 for the test, then we need to increase the other 2 late payment variables to 1 as well.

III.2 Scoring Algorithm

- In general, the scoring approaches fall into two main categories – the rule-based approach and the formula approach.

- Rule-based scoring approach – this approach refers to the algorithms that assign points or scores directly to each variable. Such algorithms in fact create a series of "if-then rules" to determine the final credit score. The advantages and disadvantages of this approach are:

    - It is an approach that is relatively simple, easy to understand, and easy to communicate and explain.
    - This approach produces a rating mechanism that can fit in well with the insurance rating and class plan structure. Therefore, it can be easily incorporated into the rating and class plan reviews. For example, actuaries can use minimum bias [10,11,12] or GLM technique [13,14] to determine the factors for each "rule" the underlies the credit variables along with the rating variables in a comprehensive class plan factor analysis.
    - One disadvantage of this approach includes the significant effort that is required to pre-determine the groupings for the rules in each variable.
    - Another disadvantage is the potential for low credibility if the number of groupings and variables increases, leading to high volatility in the results. Therefore, there are less variables used in the approach than the formula approach, which will be described next.

- Formula approach – this approach determines the score through a mathematical formula. Therefore, the key information for the approach is the determination of the weights that apply to each of the variables. The advantages and disadvantages of the approach are:

- Most of the modeling techniques, including regression, GLM [13,14], neural networks [15,16,17,18], and MARS [19,20], create formulas directly. It is therefore easier for modelers to apply the modeling results through the formula approach.
- It is easier for this approach to utilize more variables than the rule-based approach.
- One major disadvantage of this approach is that the resulting formulas are more complex and more difficult to understand by reviewers who may not have backgrounds in actuarial science and statistics. Even linear-type formulas can be complex and lengthy. Therefore, this approach often creates a "black-box" mentality around the models, especially for more complicated model generation techniques that may be utilized such as neural networks.
- Another disadvantage of the formula approach is that when more and more variables are included in the models, on occasion, the weights/coefficients to some variables become difficult to interpret in relationship to their business context and meaning. For example, formula coefficients can become counter-intuitive when a variable is expected to indicate a poorer quality risk but the model's coefficient seems to indicate the opposite. The model's complicated mathematical interactions between the variables and their related coefficients often cause such conditions. Such formula characteristics can create a challenge for companies using such models in today's regulatory environment. It is difficult to explain to regulators and consumers the mathematical basis for such model structures.

- One way to connect the two approaches (rule-based and formula) is through the delta method that we have previously described. Since the rule-based approach will assign points for each value of a credit variable, then the difference in points between two adjacent values of a variable is the delta change. Such delta changes can be derived from the formula approach as well, which will be the same as the weights for a linear formula, or the first derivative for a non-linear formula. By comparing the delta between these two approaches, the results of the two approaches can be connected or compared.

- Among the models reviewed in this study, the Fair Isaac and Company #1's proprietary models utilize the rule-based approach, while the Company #2's proprietary model employs the formula approach. Interestingly, ChoicePoint's model is a mixed approach of both profile and formulas. The ChoicePoint model presents the ScoreCard1 and ScoreCard2 as a rule-based point-assignment format, but the process appears to be more similar to the formula approach.

III.3 Score Scaling Functions and Final Score Range

- The purpose of the score scaling functions is to transform a raw score, which is typically a continuous and fractional number that predicts loss ratio, to a final score that can be used and understood more easily by end users, including underwriters, agents, publics, and regulators.

- The scaling functions have to be monotonic – that is, strictly increasing or decreasing so that one unique value for the raw score will be transformed into a unique final score.

- The selection of a scaling function is determined by the final range and the distribution of the score in the range. The scaling function can also be influenced by other criteria. An example is to benchmark the score to loss ratio relativity such as score 200 for –30% relativity, 300 for –20%, 400 for –10%, 500 for 0%,...etc.

- The scaling functions used by Fair Isaac, ChoicePoint, and Company #1's proprietary model are simple linear scaling functions, while the scaling functions used by Company #2's proprietary model are highly nonlinear.

- It is interesting that the two industry models, ChoicePoint and Fair Isaac assign higher scores to better risks, while the two proprietary models assign higher scores to worse risks. We assume that the difference has more to do with how the scores are utilized within the company's information systems than with any other factor.

III.4 Normalization Score Ranking Testing with Real Data

- In previous sections, we commented on the details of each model with regard to their variables, scoring algorithm, score scaling functions, and final calibrated score range. We also discussed a normalization process with the variable sensitivity test to compare variables' strength between models. The ultimate comparison of the models is on the final score. While there exists many similar characteristics among these models, such as the variables used in the models, they differ in areas such as scoring algorithms and score ranges. The best way to compare and evaluate various models is to test them with real data. Our experience indicates that the model results are highly influenced by the market segmentation (preferred vs. standard vs. nonstandard), demographic distribution (i.e. age, gender, marital status, etc), and geographic distribution (such as urban vs. suburban vs. rural).

- Since the model variables, scoring functions, and score ranges vary from one model to another for a book of business, a normalization process of using score ranking can be used when comparing different models. This normalization process includes the following steps: (1) score the data set; (2) sort the data points from best to worst based upon their predicted outcomes; and (3) assign the score to each data point based on the relative ranking of the predictive result. The resulting predictive model scores can then be sorted into a fixed percentile range or a range of buckets, for example, 10 equal size buckets or deciles. This process is called a decile analysis (or 5 equal size bukets for quintles, 4 equal size bukets for quartiles, etc).

- To illustrate the score ranking test, we have scored a real dataset of 10,000 data points using two Fair Isaac models – the Fair Isaac - Assist 2.0 Preferred Auto model and the Fair Isaac - Assist 2.1 HO3 model. First, we score the data by the individual model and Exhibit 8 shows the score distribution by the two models. Exhibit 9 then compares the difference in the scores between the two models. At first glance, Exhibits 8 and 9 may appear to show that the difference in the score between the two models is quite significant. However, if we rescale the final score into a decile score ranking for comparison, the results indicate that the difference between these two models is not significant. This is illustrated in Exhibit 10 where, for example, it is apparent that almost 90% of the data points have a differential within +-3 deciles between the two models.

  In addition to comparing the score disruption from one model to another, we can also use this score ranking process to test how each underlying variable affects the model's final outcomes through the delta method described previously. Instead of testing the impact on the score change as given in Exhibit 6 and Exhibit 7 we can test the impact of the variable on the score ranking change.

IV. Consideration of Selecting a Credit Score Model

When a company evaluates whether to build a proprietary credit model or select an off-the-shelf industry model, we believe that the following issues should be carefully evaluated:

- Predictive Power/Lift: The name of the game is to build a model that has strong predictive power and the ability to maximize the segmentation of better risks from poorer risks. A standard measurement that can be used to represent such predictive power and segmentation capability is the concept of a "lift" curve [5]. A lift curve is generated by sorting the score of a test set, breaking the dataset into equal-sized pieces (for example, 10 pieces/deciles), and then plotting the loss ratio/frequency/severity for each piece. We have portrayed a lift curve in Exhibit 11 using deciles as the unit of division. If a model can successfully segment better risks from poorer risks, then the curve should exhibit an increasing slope from better deciles to poorer deciles. The higher the slope, the more predictive power the model possesses. A series of benchmarks can be derived from the lift curves, which includes the loss ratio relativity for the best and the worse 5%, 10%, and 25%. Another commonly used benchmark is the ratio of the loss ratio for the worst 10% to the loss ratio of the best 10%, or the worst 25% to the best 25%. For example, in Company #1's filing, it indicates a surcharge of 45% for the worst 10% and a discount of 25% for the best 10%. This suggests a ratio of 1.45/0.75 = 1.8 for the worst 10% risks to the best 10% risk. Our experience indicates that in general the ratio of worst to best 10% for a typical credit score model is between 1.5 to 2.0

- Stability of a credit model: Another consideration when evaluating the quality of a credit scoring predictive model is the model stability, or how frequently and by how much a credit score will change from one period to another. This consideration is particularly important if the credit score is used for renewal pricing. To test the stability of a credit score model one must perform a multiyear analysis. Again, we recommend that such analyses be done using the score ranking test described previously.

- Company expertise and regulatory defensibility: Regardless of the type of model used, an insurer must be able to authoritatively speak about the model and be prepared to defend the model to customers and regulators. The degree to which a company can develop expertise about the inner workings of a model depends somewhat on whether the model is a vended model or a custom proprietary model. A custom proprietary model allows a company to better control the way in which the model is designed, developed, and implemented. And the mere fact that the model is the property of the company tends to make it more likely that the company will have greater expertise and insight into the model and its subtleties.

V. Conclusion: Is It Still a "Black Box"?

In recent years there has been a significant "tug of war" between the insurance industry and insurance regulators/consumers. The "black box" concept fueled the flames. By taking the time to examine the contents of these recent insurance filings, we have been able to gain a better understanding of the techniques and methods of the insurance industry for credit scoring. We have seen that there are more similarities between models than there are differences. Many key variables used in these models are the same. Some scores are manifested in rule-based methods while others are the result of a multivariate formula. While algorithms, scaling functions, and score ranges may vary between the models, in the end, the score represents an assessment of whether a risk is expected to be a better risk or a poorer risk with personal credit data as the primary driver for this indication.

As we have seen, most private passenger automobile and homeowner's insurers use credit scoring as a risk selection and pricing tool. Virtually no insurers use credit scoring in a vacuum; that is, credit scoring is only part of the entire process and not the sole determining factor. Given this supporting role in the insurance process and the significant evidence that insurance credit scoring works for predicting the propensity for insurance loss, it seems unlikely that insurance credit scoring will be banned throughout the country. Instead model legislation like that proposed by the National Conference of Insurance Legislators (NCOIL) seems likely to continue to serve as the basis which will provide fairness to consumers while allowing the insurance industry to use a strong predictive tool. By opening the "black box" through public discussion and analysis similar to that which is presented in this article, the public can become more comfortable with the inner workings of these models and the techniques that are utilized within them. We believe that such understanding will improve the comfort level for the use of insurance credit scores and in the end, openness and dialogue should help resolve some of the differences surrounding the issue.

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EXHIBITS

Exhibit 1
List of Insurers Using Credit Scores in Rating - Virginia Bureau of Insurance

This list was delivered to the authors as a draft document as of November 2002. It was obtained from the Virginia Bureau of Insurance and has not been formally verified.
The list may include the names of insurers who no longer use credit scoring in rating or may not include the names of insurers that have recently begun to use credit scoring.

Company Name	Line(s) of Insurance
AIG Group (AIG National Insurance Company; AIU Insurance Company; American Home Assurance Company; American International South Insurance Company)	Personal Auto
Agency Insurance Company of Maryland	Personal Auto
Allstate Insurance Company	Personal Auto and Homeowners
Allstate Indemnity Company	Personal Auto and Homeowners
American & Foreign Insurance Company	Homeowners
American Motorists Insurance Company	Personal Auto and Homeowners
Auto-Owners Insurance Company	Personal Auto - Pending
Deerbrook Insurance Company	Personal Auto
Farmers Insurance Exchange	Personal Auto and Homeowners
First Liberty Insurance Corporation	Personal Auto
Globe Indemnity Company	Personal Auto
Harleysville Mutual Insurance Company	Homeowners
Harleysville Preferred Insurance Company	Homeowners
Hartford Accident and Indemnity Company	Personal Auto
Homesite Insurance Company	Homeowners
Horace Mann Insurance Company	Personal Auto and Homeowners
Horace Mann Property and Casualty Ins Company	Personal Auto and Homeowners
Integon National Insurance Company	Personal Auto
Kansas City Fire and Marine Insurance Company	Personal Auto and Homeowners (USP)
Kemper Auto and Home Insurance Company	Personal Auto
Kemper Independence Insurance Company	Personal Auto
Liberty Mutual Fire Insurance Company	Personal Auto
Main Street America Insurance Company	Personal Auto
Mercury Casualty Company	Personal Auto
Metropolitan General Insurance Company	Personal Auto
Mid-Century Insurance Company	Personal Auto
Montgomery Ward Insurance Company	Personal Auto
National Grange Mutual	Personal Auto
Nationwide Mutual Fire Insurance Company	Personal Auto
Nationwide Mutual Insurance Company	Personal Auto
Owners Insurance Company	Personal Auto
Prudential General Insurance Company	Personal Auto
Royal Indemnity Company	Homeowners
Royal Insurance Company of America	Personal Auto
Safeguard Insurance Company	Personal Auto
State Auto Property and Casualty Ins. Company	Personal Auto
Teachers Insurance Company	Personal Auto
Tri-State Insurance Company	Personal Auto
United Services Automobile Association	Personal Auto and Homeowners
USAA Casualty Insurance Company	Personal Auto and Homeowners

Exhibit 2
Summary of Credit Score Models Reviewed

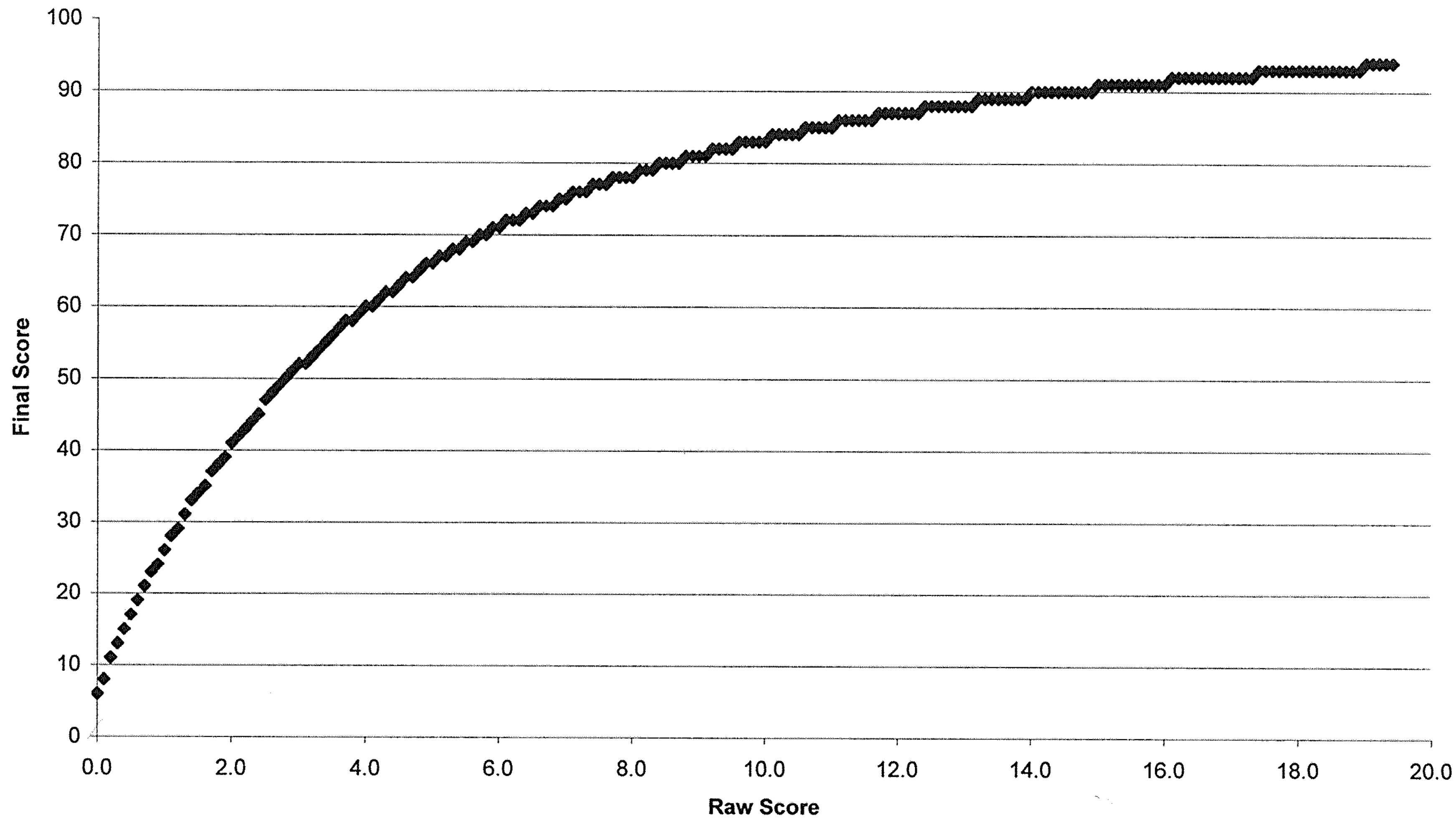
Company	LOB	2002 Net Written Premium Derived from AM Best [8]	Industry vs Proprietary Models	# of Variables	Scoring Functions	Score Range*	Higher Score
Company #1	Auto	>=$5 Billions	Proprietary	10	Profiling	84-1078	Worst Risks
Company #1	Home	>=$5 Billions	Proprietary - Same as Auto	10	Profiling	84-1078	Worst Risks
Company #2	Auto	>=$5 Billions	Proprietary	36	Scoring	1-100	Worst Risks
Company #3	Auto	<=$1 Billion	Fair Isaac - Assist 2.0, Preferred Greater than Min Limits	12	Profiling	357-818	Better Risks
Company #4	Auto	>$1 and <$5 Billions	Fair Isaac - InScore 2.0, Standard Greater than Min Limits	11	Profiling	389-806	Better Risks
Company #5	Auto	<=$1 Billion	ChoicePoint	29 for Thin and 37 for Thick	Scoring	220-997	Better Risks
Company #6	Auto	>$1 and <$5 Billions	ChoicePoint	29 for Thin and 37 for Thick	Scoring	220-997	Better Risks
Company #7	Auto	<=$1 Billion	ChoicePoint	29 for Thin and 37 for Thick	Scoring	220-997	Better Risks
Company #8	Auto	>$1 and <$5 Billions	ChoicePoint	29 for Thin and 37 for Thick	Scoring	220-997	Better Risks
Company #9	Auto	>=$5 Billions	Fair Isaac - Assist 2.0, Preferred Auto Min Limits	11	Profiling	326-845	Better Risks
Company #9	Home	>=$5 Billions	Fair Isaac - Assist 2.1, HO3	13	Profiling	200-884	Better Risks

* The score ranges given here are the theorical score ranges, not the likely score ranges for a typical book of business.

Exhibit 3
Number of Credit Model Variables in Each Group

Company	LOB	Industry vs Proprietary Models	(1) Late Payment/Past Due/Deliquent Information	(2) Unsatifactory, Default, Bad Debt Info	(3) Public Derogatory Information	(4) Collection Information	(5) Inquiry Information	(6) Other - Account Informatio, Levarage Ratio, and Others
Company #1	Auto	Proprietary	3	0	1	1	1	4
Company #1	Home	Proprietary - Same as Auto	3	0	1	1	1	4
Company #2	Auto	Proprietary	17	1	1	0	3	14
Company #3	Auto	Fair Isaac - Assist 2.0, Preferred Greater than Min Limits	5	2	2	1	1	3
Company #4	Auto	Fair Isaac - InScore 2.0, Standard	3	4	1	1	0	2
Company #5	Auto	ChoicePoint	2 for Thin and 4 for Thick	7 for Thin and 6 for Thick	2 For Thin	1 for Thick	2 for Thin and 2 for Thick	10+ for both Thin and Thick
Company #6	Auto	ChoicePoint	2 for Thin and 4 for Thick	7 for Thin and 6 for Thick	2 For Thin	1 for Thick	2 for Thin and 2 for Thick	10+ for both Thin and Thick
Company #7	Auto	ChoicePoint	2 for Thin and 4 for Thick	7 for Thin and 6 for Thick	2 For Thin	1 for Thick	2 for Thin and 2 for Thick	10+ for both Thin and Thick
Company #8	Auto	ChoicePoint	2 for Thin and 4 for Thick	7 for Thin and 6 for Thick	2 For Thin	1 for Thick	2 for Thin and 2 for Thick	10+ for both Thin and Thick
Company #9	Auto	Fair Isaac - Assist 2.0, Preferred Auto Min Limits	4	2	1	1	1	2
Company #9	Home	Fair Isaac - Assist 2.1, HO3	3	2	2	2	1	3

Exhibit 4
Company #2 Proprietary Model's
Score Scaling Function



Pages 275-282 have been removed.
For Exhibit 4 raw data, see the printed publication.

Exhibit 5
Impact of Variables on Credit Scores Suggested by the Models

Variables	More	Recent
Late Payment/Past Due/Deliquent Information	Worse	Worse
Unsatifactory, Default, Bad Debt Information	Worse	N/A
Public Derogatory Information	Worse	Worse
Collection Information	Worse	Worse
Inquiry Information	Worse	N/A
Other - Account Informatio, Levarage Ratio, and Others	Varies	

Exhibit 6
An Example of Testing Variable Strength with the Delta Method

I. Change in Average Months in File of All Accounts

Change in the Final Score

Average Months Change		Fair Isaac - Assist 2.0, Preferred Auto Min Limits			Fair Isaac - Assist 2.0, Preferred Greater than Min Limits		Fair Isaac - Assist 2.1, HO3	
From	To	Score < 625	Score <725 and >=625	Score >=725	Score < 730	Score >= 730	Score <775	Score >= 775
0-20	21-23	1	1	2	2	5	2	3
21-23	24-29	4	5	6	6	15	10	14
24-29	30-32	6	7	9	9	20	12	17
30-32	33-39	1	1	2	2	5	2	3
33-39	40-41	1	1	2	2	5	3	4
40-41	42-47	1	1	2	1	2	2	3
42-47	48-53	8	10	12	14	32	19	26
48-53	54-59	4	5	6	8	17	10	14
54-59	60-65	2	2	3	3	7	5	7
60-65	66-71	1	1	2	2	5	2	3
66-71	72-83	4	5	6	5	12	7	10
72-83	84-89	1	1	2	1	2	3	4
84-89	90-95	1	1	2	2	5	2	3
90-95	96-105	1	1	2	2	5	3	4
96-105	106-115	1	1	2	1	2	2	3
106-115	116-119	1	1	2	2	5	2	3
116-119	120-139	1	1	2	1	2	3	4
120-139	140-159	1	1	2	2	5	2	3
140-159	160-179	1	1	2	2	5	3	4
160-179	180-199	1	1	2	1	2	2	3
180-199	200-219	1	1	2	2	5	2	3
200-219	220-239	1	1	2	2	5	3	4
220-239	240-359	1	1	2	1	2	2	3
240-359	360-479	1	1	2	2	5	3	4
360-479	480-599	1	1	2	1	2	2	3
480-599	600+	1	1	2	2	5	2	3

II. Change in Number of Inquiries

Change in the Final Score

Number of Inquiries		Fair Isaac - Assist 2.0, Preferred Auto Min Limits			Fair Isaac - Assist 2.0, Preferred Greater than Min Limits		Fair Isaac - Assist 2.1, HO3	
From	To	Score < 625	Score <725 and >=625	Score >=725	Score < 730	Score >= 730	Score <775	Score >= 775
0	1	-7	-8	-11	-5	-7	-8	-17
1	2	-12	-14	-18	-11	-15	-13	-29
2	3	-15	-18	-23	-13	-18	-17	-39
3	4	-16	-19	-24	-14	-19	-18	-41
4	5+	-6	-7	-9	-5	-7	-6	-15

Exhibit 7

Normalization of the Testing Variable Strength Results in Exhibit 6 *

I. Change in Average Months in File of All Accounts

Ratio of the Changes in the Final Score Using the First Change as the Base *

Average Months Change			Fair Isaac - Assist 2.0, Preferred Auto Min Limits			Fair Isaac - Assist 2.0, Preferred Greater than Min Limits		Fair Isaac - Assist 2.1, HO3	
From	To		Score < 625	Score <725 and >=625	Score >=725	Score < 730	Score >= 730	Score <775	Score >= 775
0-20	21-23	**	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*	*1.0*
21-23	24-29		4.0	5.0	3.0	3.0	3.0	5.0	4.7
24-29	30-32		6.0	7.0	4.5	4.5	4.0	6.0	5.7
30-32	33-39		1.0	1.0	1.0	1.0	1.0	1.0	1.0
33-39	40-41		1.0	1.0	1.0	1.0	1.0	1.5	1.3
40-41	42-47		1.0	1.0	1.0	0.5	0.4	1.0	1.0
42-47	48-53		8.0	10.0	6.0	7.0	6.4	9.5	8.7
48-53	54-59		4.0	5.0	3.0	4.0	3.4	5.0	4.7
54-59	60-65		2.0	2.0	1.5	1.5	1.4	2.5	2.3
60-65	66-71		1.0	1.0	1.0	1.0	1.0	1.0	1.0
66-71	72-83		4.0	5.0	3.0	2.5	2.4	3.5	3.3
72-83	84-89		1.0	1.0	1.0	0.5	0.4	1.5	1.3
84-89	90-95		1.0	1.0	1.0	1.0	1.0	1.0	1.0
90-95	96-105		1.0	1.0	1.0	1.0	1.0	1.5	1.3
96-105	106-115		1.0	1.0	1.0	0.5	0.4	1.0	1.0
106-115	116-119		1.0	1.0	1.0	1.0	1.0	1.0	1.0
116-119	120-139		1.0	1.0	1.0	0.5	0.4	1.5	1.3
120-139	140-159		1.0	1.0	1.0	1.0	1.0	1.0	1.0
140-159	160-179		1.0	1.0	1.0	1.0	1.0	1.5	1.3
160-179	180-199		1.0	1.0	1.0	0.5	0.4	1.0	1.0
180-199	200-219		1.0	1.0	1.0	1.0	1.0	1.0	1.0
200-219	220-239		1.0	1.0	1.0	1.0	1.0	1.5	1.3
220-239	240-359		1.0	1.0	1.0	0.5	0.4	1.0	1.0
240-359	360-479		1.0	1.0	1.0	1.0	1.0	1.5	1.3
360-479	480-599		1.0	1.0	1.0	0.5	0.4	1.0	1.0
480-599	600+		1.0	1.0	1.0	1.0	1.0	1.0	1.0

II. Change in Number of Inquiries

Ratio of the Changes in the Final Score Using the First Change as the Base *

Number of Inquiries			Fair Isaac - Assist 2.0, Preferred Auto Min Limits			Fair Isaac - Assist 2.0, Preferred Greater than Min Limits		Fair Isaac - Assist 2.1, HO3	
From	To		Score < 625	Score <725 and >=625	Score >=725	Score < 730	Score >= 730	Score <775	Score >= 775
0	1	**	*-1.0*	*-1.0*	*-1.0*	*-1.0*	*-1.0*	*-1.0*	*-1.0*
1	2		-1.7	-1.8	-1.6	-2.2	-2.1	-1.6	-1.7
2	3		-2.1	-2.3	-2.1	-2.6	-2.6	-2.1	-2.3
3	4		-2.3	-2.4	-2.2	-2.8	-2.7	-2.3	-2.4
4	5+		-0.9	-0.9	-0.8	-1.0	-1.0	-0.8	-0.9

* Results given in this exhibit is the ratio of each change to the first change in the same column

** This row is used as the base to normalize the changes.

Exhibit 8
Score Distribution Comparison between a Auto Model and a Home Model by Fair Isaac

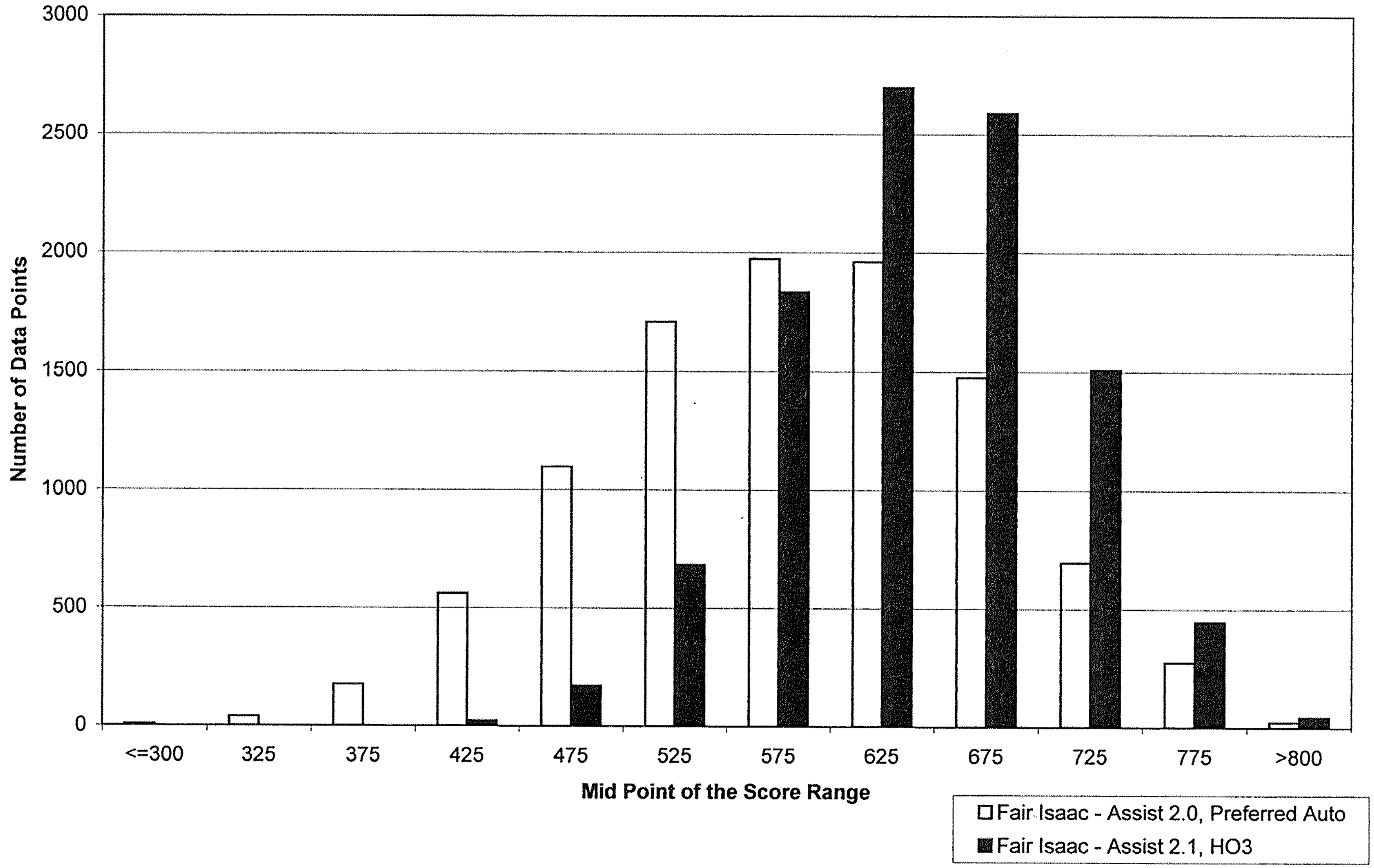


Exhibit 9

Distribution of the Difference Between a Fair Isaac Auto Score and a Fair Isaac Home Score

	Mid Point of the Difference*	Number of Data Points	% of Data Points
	-175	2	0.02%
	-125	185	1.85%
	-75	1452	14.52%
	-25	2979	29.79%
	25	2906	29.06%
	75	1861	18.61%
	125	600	6.00%
	175	15	0.15%
Total		10000	100.00%

* Difference = (Fair Isaac Assist 2.1, HO3 Score) - (Fair Isaac Assist 2.0, Preferred Auto Score)

Exhibit 10

Distribution of the Difference Between a Fair Isaac Auto Score and a Fair Isaac Home Score in Decile Ranking

	Difference in Decile Score Ranking	Number of Data Points	% of Data Points
	-9	0	0.0%
	-8	0	0.0%
	-7	1	0.0%
	-6	23	0.2%
	-5	99	1.0%
	-4	259	2.6%
	-3	599	6.0%
	-2	1068	10.7%
	-1	1646	16.5%
	0	2702	27.0%
	1	1569	15.7%
	2	1024	10.2%
	3	557	5.6%
	4	318	3.2%
	5	115	1.2%
	6	20	0.2%
	7	0	0.0%
	8	0	0.0%
	9	0	0.0%
Total		10000	100.0%

* Difference = (Fair Isaac Assist 2.1, HO3 Score Ranking) - (Fair Isaac Assist 2.0, Preferred Auto Score Ranking)

Exhibit 11
A Loss Ratio Lift Curve

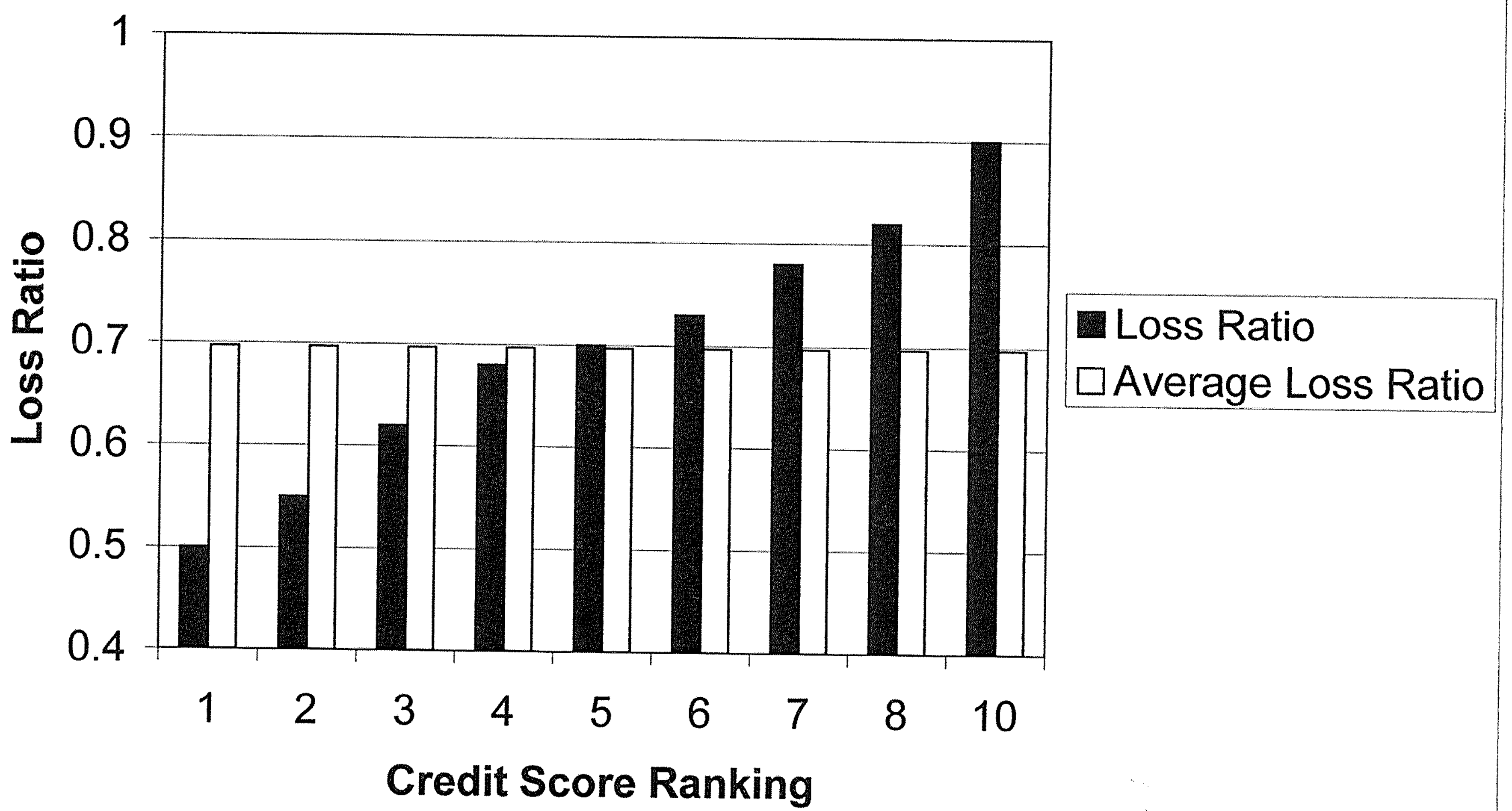


Exhibit 11
A Loss Ratio Lift Curve
Data

Score Ranking	Loss Ratio	Average Loss Ratio
1	0.5	0.697
2	0.55	0.697
3	0.62	0.697
4	0.68	0.697
5	0.7	0.697
6	0.73	0.697
7	0.78	0.697
8	0.82	0.697
10	0.9	0.697