A Discussion of Risk Assessment Methods for the German Automobile Insurance Industry

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A DISCUSSION OF RISK ASSESSMENT METHODS FOR THE
GERMAN AUTOMOBILE INSURANCE INDUSTRY

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ABSTRACT

The aim of this paper is to discuss different methods for risk assessment in the
German automobile industry. We present the traditional approach for classifying
risks, which is actually applied in the German market, and discuss one crucial dif-
ficulty inherent to this approach for proper risk assessment. Then, we describe the
“insurance scoring” approach as used in the U.S. insurance market, which leads us
to suggest scoring techniques as a risk assessment method for the German automo-
bile insurance industry. Finally, we discuss the benefits and problems of scoring in
the context of automobile insurance.

1. INTRODUCTION

A proper assessment of the size of an insurance company’s risk or, to put it dif-
ferently, a good prediction of future expected claims, is of vital importance to the
company for several reasons. First, correct assessment of future expected claim
size is very important in calculating appropriate premiums, thus affecting profit-
ability. Second, by charging risk-adequate premiums, the insurance company can
avoid adverse selection, i.e., the loss of good (low claim potential) insurance cus-
tomers because its premiums are too high priced (see Growitsch et al., 2006). A
good risk assessment might even allow undercutting the premium level in certain
lines of business, leading to a gain of market share in those segments. Third,
proper risk assessment is becoming of increasing importance to rating agencies
(see, e.g., S&P, 2005). A good rating is essential to lower refinancing costs of the
insurance company and it also signals the company’s reliability, which can en-
hance customer loyalty. Finally, the ability to select certain risks based on ad-

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Advanced risk assessment can be helpful in lowering overall portfolio risk (lower volatility, reduced tail risk) and thus reducing equity capital costs due to decreased regulatory capital demand. This required capital is, e.g., necessary under new supervisory regimes such as Solvency II.

In this working paper, we study the usage of risk assessment methods in the German automobile insurance industry, taking a look at both liability and comprehensive insurance. The German automobile insurance market is characterized by high competitive pressure as well as high combined ratios and, hence, by low profitability (see GDV, 2006, pp. 101–103). In Germany, automobile insurance industry risks are traditionally classified on the basis of a great many risk factors, such as, for example, occupation, type of car, and region. Additionally, there are different bonus-malus classes, depending on previous claim history. Thus, the risks are assigned to several thousand different tariff classes (see Mack, 2002, p. 161). The problem with this approach is that it leads to heavy data fragmentation with many classes containing only few risks and often showing no or only little claim experience, making it difficult to calculate risk adequate prices based on claim history for these tariff classes. To date, several methods are used to overcome this problem. For example, cluster analysis attempts to identify tariff classes with similar claim expectations so as to achieve a better basis for calculating premiums (see, e.g., Yeo et al., 2001). Other methods involve interpolation (see Dugas et al., 2003) or the employment of a larger database (see Mayer, 2002, p. 59).

Here, we present an alternative risk assessment method for the German automobile insurance industry, one based on risk scoring similar to that used in the credit industry. The U.S. insurance market uses an approach called “insurance scoring” (see, e.g., Hartwig/Wilkinson, 2003). Insurers derive an “insurance score” for each potential insured by weighting certain characteristics from the applicant’s credit history, for example, delinquent loan payments and number, if any, of collection actions (see Monaghan, 2000, pp. 82–86). The underlying credit record is obtained from large national credit information providers. The insurance company uses the score thus derived in combination with other factors to evaluate the applicant’s automobile insurance risk. The main reason for using credit history data is to obtain information that will aid in evaluating unobservable factors, such as carefulness in driving (see Monaghan, 2000; Wu/Guszcza, 2003).
The approach we suggest for the German automobile insurance market is to build such a score based not only on information provided by credit history, but also using all the other information the insurance company already has available and is permitted to use. For the assessment of risks (the scoring), we suggest using methods employed by the credit industry, e.g., regression analysis or more advanced techniques such as neural networks. The aim is to find functional dependence between the observed risk realization and the observable risk factors, which would allow the insurer to more accurately estimate future claim size. This scoring approach circumvents the problem mentioned above, that is, the problem of too many tariff classes, many of which containing too little claim history to be useful in setting rates. For the risk evaluation we propose, the entire data set, not just the segregated data (tariff classes), is used as a starting point for data analysis. The main difference between our approach and those in current use is that our method will look for subgroups with the same expected claim size a priori, instead of splitting up the data and then trying to identify and merge tariff classes with comparable risk characteristics and claim sizes. The following paper discusses in more detail the differences, benefits, and detriments of the suggested approach compared to more traditional techniques.

We proceed as follows: in Section 2 we present the approach to risk assessment usually applied by the German automobile insurance industry, the problems associated with this approach and the methods used to date for mitigating them. In Section 3, we illustrate the “insurance scoring” approach as applied in the U.S. insurance market. Then, in Section 4, we describe how using the scoring approach can avoid the problem of tariff classes with little or no claim history. We discuss advantages and disadvantages of this method, and also touch upon the special issue of unobservable factors in risk assessment. We conclude in Section 5.

2. TRADITIONAL RISK ASSESSMENT IN THE GERMAN AUTOMOBILE INSURANCE INDUSTRY

The traditional approach to classifying risk in automobile liability insurance is to assign an insured to a tariff class. The various tariff classes are based on many criteria, including, for example, type of car, insured’s occupation, region (urban vs. rural), and driving history. This classification approach has resulted in the German automobile liability insurance tariff of 1998, which contains 3 occupa-
tion groups, 16 types of cars, 12 regional classes, and 22 bonus-malus classes. This adds up to 12,672 different tariff classes (see Mack, 2006, p. 25). That is a huge number of tariff classes and many of them have few or no insureds with claim experience, especially in the case of small automobile insurance portfolios. Thus, it is difficult to calculate an appropriate premium for these tariff classes as there is little or no claim experience to base it on (see Mack, 2002, p. 162).

To demonstrate the complexity that arises from this classification method and the resultant problem of empty or near empty tariff classes, we provide the following example using a stylized data set. The data set consists of data for 1,000 insureds. Of these insureds, 25% show a claim. To illustrate the traditional hierarchical classification, we use a variable that represents claim size and two binary risk factors—that can be region (urban vs. rural) or garage usage (garage vs. no garage) as representatives of the risk factors considered by insurers. The third variable is an interval-scaled variable (e.g., based on the age of the insured) with seven intervals.

Employing these three explanatory variables, we obtain a total of 28 tariff classes. Table 1 sets out the number of insureds assigned to each tariff class. The number of claims per tariff class is shown in parentheses. As would be the case in “real-world” car insurance data, there are some cells without any insureds. Also, there is one tariff class containing two insureds, but no claim experience.
<table>
<thead>
<tr>
<th>Factor I</th>
<th>no (0)</th>
<th>yes (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor II</td>
<td>no (0)</td>
<td>yes (1)</td>
</tr>
<tr>
<td>Factor III</td>
<td>no (0)</td>
<td>yes (1)</td>
</tr>
<tr>
<td>1</td>
<td>2(1)</td>
<td>0(0)</td>
</tr>
<tr>
<td>2</td>
<td>95(38)</td>
<td>200(63)</td>
</tr>
<tr>
<td>3</td>
<td>22(7)</td>
<td>200(44)</td>
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<tr>
<td>4</td>
<td>14(2)</td>
<td>96(29)</td>
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<td>5</td>
<td>6(2)</td>
<td>43(12)</td>
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<tr>
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<td>3(1)</td>
<td>22(7)</td>
</tr>
<tr>
<td>7</td>
<td>0(0)</td>
<td>4(1)</td>
</tr>
<tr>
<td></td>
<td>142(51)</td>
<td>565(156)</td>
</tr>
</tbody>
</table>

Table 1: Stylized data example—Assignment of insureds and claims to the different tariff classes

<table>
<thead>
<tr>
<th>Factor I</th>
<th>no (0)</th>
<th>yes (1)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>yes (1)</td>
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<tr>
<td>Factor III</td>
<td>no (0)</td>
<td>yes (1)</td>
</tr>
<tr>
<td>1</td>
<td>990.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>1126.55</td>
<td>1100.57</td>
</tr>
<tr>
<td>3</td>
<td>1309.41</td>
<td>848.96</td>
</tr>
<tr>
<td>4</td>
<td>136.21</td>
<td>1179.07</td>
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<td>5</td>
<td>3726.83</td>
<td>1279.81</td>
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<td>6</td>
<td>922.33</td>
<td>2022.14</td>
</tr>
<tr>
<td>7</td>
<td>0.00</td>
<td>1282.25</td>
</tr>
<tr>
<td></td>
<td>1160.87</td>
<td>1075.65</td>
</tr>
</tbody>
</table>

Table 2: Stylized data example—Average claim size for the different tariff classes

Table 2 shows the average claim size for each tariff class in our example. This average claim size can be used to estimate future claim size, and thus is a basis for calculating risk-adequate insurance premiums. This approach is not unreasonable because for most of the tariff classes there is a claim history. However, the question arises: How appropriate (or, for that matter, accurate) is it to base premium rates on average claim size when there are very few claims to average?
An even harder question to answer, of course, is how to set a proper premium for a tariff class that has no previous claim experience.

One way of coping with this problem is to access a larger database and for the German market, there is one, that made available by the German insurance association (GDV—Gesamtverband der Deutschen Versicherungswirtschaft e.V.). With additional claim data from many other insurance companies, the problem of classes with few or no cases can be mitigated (see Mayer, 2002, p. 59). However, this approach is not without problems either, as the additional data pool might be significantly different from the insurer’s own automobile liability portfolio, possibly leading to inaccurate premium rate calculations.

An alternative method, taken from the field of statistical data analysis, is cluster analysis (see Mack, 2002, p. 123). This method compares the expected claim sizes for different tariff classes, with the goal of identifying clusters in the data with similar expected claim sizes and then merging these tariff classes to arrive at an improved basis for premium calculation. The algorithm applied for cluster analysis can work from the top down (from the whole group of tariff classes to smaller consistent subgroups) or from the bottom up (from the smallest entities to larger nearly identical data clusters). Similar subgroups are identified by measuring the distances between different smaller entities, meaning that the expected claims sizes are compared using tests of equality (see, e.g., Mayer, 2002, p. 18). Based on this distance information, subgroups of data are either merged into clusters or separated from each other. However, in the case of too few or no claim experience data, cluster analysis as an aggregation method does not work very well and should not be used (see Mack, 2002, p. 139).

Further options for estimating the expected claim size of empty or nearly empty tariff classes include interpolation or nonparametric estimation methods. Under the interpolation approach, nearby tariff classes with adequate amounts of data are identified and then, in the next step, the unknown information for the classes in-between the classes with known information is estimated using interpolation. The idea is that there is a simple linear relationship between the adjacent data entities (see Dugas et al., 2003). From the field of nonparametric data analysis, one can use distance-related weights, an approach closely akin to kernel density estimation techniques. In this approach, one assumes that the next neighbors can be used to estimate the expected claim size of a tariff class with sparse data. The
most rational way would be to use spheres with weights that decline as the tariff classes become more distant from the considered tariff class. Of course, this approach only works if there is enough data around the considered tariff class (for an overview, see Härdle et al., 2004).

3. THE APPLICATION OF INFORMATION FROM CREDIT HISTORY TO RISK ASSESSMENT IN THE U.S. INSURANCE MARKET

In contrast to the German system, where risk assessment is based on characteristics such as type of car, occupation, or region, U.S. automobile insurers use an approach known as “insurance scoring,” which additionally takes into consideration the applicant’s credit history in calculating risk-adequate premiums, a method also employed in the U.S. homeowner insurance industry. The credit history is obtained from large credit information providers (e.g., Experia or Fair Isaac) and the “scoring” procedure involves weighting certain characteristics from the credit record (amounts past due or collection records) and using this information together with the standard classification characteristics (e.g., region or type of car) with the goal of achieving a meaningful prediction of future claims (see Hartwig/Wilkinson, 2003, p. 2). The underlying assumption is that there is a meaningful relationship between the credit score and the probability of a car accident or, in the homeowner insurance context, fire loss. There has been a great deal of discussion and debate on the use of credit history to calculate premiums in the U.S. market (see, e.g., Lee et al., 2005; Birnbaum, 2007). Those in favor argue that people who pay back loans are expected to be more careful in other aspects of their lives, too, such as driving, and, correspondingly, that a person with a bad credit history is more likely to be a less careful driver. Those who argue against using credit history for determining insurance premiums claim that a person’s credit history and the probability of him or her having a car accident are so distinct from each other that there cannot be any relationship between them. Further, the opponents also point out that using credit history to set insurance rates will discriminate against people with bad credit history in that they will get no insurance coverage or only under very unfavorable conditions.

Using credit history to set premium rates is not allowed in some states of the United States due to contrary viewpoints concerning the reliability of this sort of information for predicting claim probabilities and also due to concerns about violating anti-discrimination laws (see, e.g., Birnbaum, 2007). However, there have
been some studies that attempt to analyze whether there is a functional relationship between credit history and claim probability. Monaghan (2000) studies the relation between car insurance losses and credit history. A record of insured persons was sent to a credit information provider. For every insured for whom credit information was available, these data were added. Then, for these insureds, the univariate relationship between different characteristics from the credit history and the loss ratio was examined. The results showed that there was a statistically significant relation between information from the credit record and the loss ratio for many variables. For example, for a rising number of collection records the observed loss ratio also rose. Wu/Guszczza (2003) found similar results in their multivariate regression analysis for a comparable subject of investigation. Brockett/Golden (2007) surveyed a large number of past studies with respect to the biochemical and psychobehavioral relation between risk-taking behavior in financial matters (credit score) and in driving (insured auto losses). These authors also propose that there is a relationship between credit behavior and driving habits.

It can be concluded that using credit history to set premium rates involves using a measurable factor to obtain information about less-measurable factors, such as an affinity for risky driving. Thus, from information from credit history can be obtained an explanatory variable for the probability of a car accident because the credit history can, on average, indicate a type of general prudence, or lack thereof, for a large fraction of insureds. Otherwise, the relationship between credit history and the likelihood of a car accident is not as plausible (because it can deliver only indirect information) as other aspects of automobile risk, such as type of car or region. Therefore, credit history information should be used with some caution in setting insurance premium rates.

From the U.S. “insurance scoring” experience, we can glean two important aspects of risk assessment in automobile insurance. In general, it would be helpful to find variables that could provide information about soft factors, e.g., driving skills or an affinity for risky driving. One data source that can provide at least an indication of the insured’s risk as regards these factors is the insured’s credit history as it is some evidence of the person’s general reliability. In particular, in Germany, scoring could be a possible way of coping with the problem of empty or near empty tariff classes and the challenge of deriving an appropriate premium for those tariff classes.
4. A DISCUSSION OF SCORING TECHNIQUES AS A RISK ASSESSMENT METHOD FOR THE GERMAN AUTOMOBILE INSURANCE INDUSTRY

In the following section, we discuss an approach based on scoring techniques that can be an alternative to the risk assessment methods applied to date in the German automobile insurance market. The functionality of the approach will be demonstrated by the same data example set out in Section 2. Then, the advantages and disadvantages of this method are compared to the traditional tariff class system. Further, the problem of unobservable factors in risk assessment for automobile insurance is examined.

The main difference between our proposed approach to risk classification and that based on tariff classes as applied in the German automobile insurance is that in our approach no tariff classes are needed. Instead, the idea is to find a functional relationship between the characteristics of the insured and claim frequency as well as claim severity. The aim of this method is an up-front identification of subgroups with the same score, meaning that they are equivalent in both risk size and thus in expected claim size. We assume that risks with different characteristics can have a similar level of risk. In contrast, within the German tariff system, setting premium rates usually involves merging different tariff classes with comparable risk levels after separating them according to different characteristics. The main difference between this system and the “insurance scoring” approach used in the U.S. insurance market is the additional use of scoring (weighting) techniques not only for information from the credit history but also that gleaned from looking at all other known characteristics.

In principle, to determine expected claim size (the risk level), two components are needed: the claim frequency, or the probability of a claim, and the claim severity (see Renshaw, 1994, p. 265). The expected claim size can thereby be derived by the probability for one (or more) claim(s) within the next year multiplied by the expected sum of the claim(s). The probability for the occurrence of claims can be estimated using, e.g., a logit regression model, which is common practice in the insurance industry because it results in a multiplicative tariff structure. The claim size can be calculated, e.g., using multivariate regression. For our purpose, to determine the risk level, we can apply the following formula:

\[ SV_i = E(CS_i) = \pi_i \times CS_i , \]  

(1)
where \( SV_i \) stands for the score value or the risk level, \( E(CS_i) \) is the expected claim size, \( \pi_i \) is the probability of one or more claim event(s), and \( CS_i \) is the predicted sum of claims if (an) accident(s) occur(s) next year. For the purpose of demonstration, we use the same stylized data as set out in Section 2.

<table>
<thead>
<tr>
<th>Claim</th>
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<th>Factor II</th>
<th>Factor III</th>
</tr>
</thead>
<tbody>
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<td>0</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>66</td>
</tr>
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<td>0</td>
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<td>1</td>
<td>26</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>24</td>
</tr>
<tr>
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<td>0</td>
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<tr>
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<td>14318</td>
<td>0</td>
<td>1</td>
<td>57</td>
</tr>
</tbody>
</table>

Table 3: Scoring approach—Claim probability and claim size

Table 3 sets out an extract from the data example. The first column contains the information about the claim occurrence. The value “1” means that there was at least one claim for the considered insured during the time period in question; “0” means that there was no claim. The second column contains the overall claim size and Columns 3 to 5 show for every insured the observed values of the explanatory factors, which can be, e.g., the insured’s garage use or his or her age.

To estimate the probability of a claim within one year we use the information on claim occurrence in Column 1 and Factors I to III as explanatory variables \( x_{ij} \) in a logit regression model (see, e.g., Beirlant et al., 1991, p. 290):

\[
SV_i = \log \left( \frac{\pi_i}{1 - \pi_i} \right) = \sum_j x_{ij} \beta_j ,
\]

which leads us to a value for the probability (or the odds ratio) by way of the following formula:
\[ \pi_i = \frac{e^{S_i}}{1 + e^{S_i}}. \]  \hspace{1cm} (3)

After determination of the parameters \( \beta_j \) and with the help of the available data \( x_{ij} \), these parameters can be used to estimate the values of \( S_i \) and thus the probability for one or more claims \( \pi_i \) by new automobile insurance applicants or for existing contracts in the context of a portfolio reevaluation.

To derive a model that can predict claim size, one can, of course, use only those cases with claim experience. From the cases shown in Table 3, we use the values of Column 2 (claim size) if Column 1 shows the value “1” and, again, Columns 3 to 5 (Factors I to III) as explanatory variables \( x_{ij} \). The simplest solution is to apply a regression model (see, e.g., Mayer, 2002, p. 15):

\[ CS_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3}. \]  \hspace{1cm} (4)

The aim is to determine the parameters \( \beta_j \), which can be used, similar to the model for the claim probabilities, within a prediction model for determining the claim size. For a new applicant, we can now estimate the expected claim size by using Equation (1). This expected claim size will be the basis for the calculation of a risk-adequate premium.

In principle, this approach makes it unnecessary to assign a risk to a specific tariff class, as the pure risk premium can be estimated directly. If it is necessary for marketing or advertising purposes, however, certain ranges of expected claims can be summarized into a tariff class, but instead of there being several thousand of these, as is now the case in Germany, the number of tariff classes can be reduced to a meaningful number. The method can help to appropriately assess the risk (expected claims for an insured individual) and to calculate premiums that are both fair and sufficient to settle all claims occurring within the next year. Moreover, the method can be used to separate the insurer’s policyholders into tariff classes with almost similar levels of risk (see Stroinski/Currie, 1989, p. 35) without fragmenting the data into a great many small groups. In this way, insured persons with very different characteristics but having the same risk level can be treated consistently. The main advantage of this approach compared to the current system in the German automobile insurance industry is that there is no need to build subgroups, and then arrange them according to mean claim size; instead,
the risk assessment is performed more naturally at the beginning of the process. Further, improved risk-adequate pricing will allow the insurer to mitigate the effects of adverse selection and to gain a competitive advantage over other insurers. For example, good risks will stay with the insurer if competitive and risk-adequate premiums are offered. The fact that the German automobile insurance industry already practices premium differentiation with respect to different risk factors will make it easier to implement our suggested method in this industry than it would be in other branches of insurance (e.g., life insurance). Of course, this method is not without certain problems and potential pitfalls. These are discussed below.

The presented models are simplifications (see, e.g., Beirlant, 1991, pp. 299–300). For example, a logit-model can make predictions concerning the occurrence of one or more claims versus no claim, but cannot provide information on how probable the incidence of the second or the third claim for the next period is. It thus may be more realistic to use a count distribution model, as, e.g., a Poisson or negative-binomial distribution model (see, e.g., Dionne/Vanasse, 1989). Also, to predict claim size, more sophisticated models and data mining techniques can be applied, as, e.g., neural networks (see, e.g., Bigus, 1996; Chapados et al., 2002).

One possible problem is that the applied models might not fit the data, meaning that the models are not suitable for detecting patterns in the data and the determined laws (e.g., the $\beta$ of the above presented regression models) are biased and hence deliver poor prediction results for the risk size in general. First, one can test whether the parameters $\beta$ differ significantly from zero, and thus are meaningful in predicting the risk. This can be done using the Wald-test (see Beirlant et al., 1991, p. 294). An alternative is to use the above mentioned advanced classification techniques. Another possibility for model improvement is using outlier analysis to check whether outliers are distorting the results. If so, these outliers can be omitted or used with a censored value of claim size when determining the scoring model. Further, the estimated model might be a bad fit for certain subgroups, for example, the model provide a good fit for urban driver but not for drivers from a rural area. One can solve this problem by applying a test data set to check if the model works well for the overall data. If there are obvious differences from reality, the scoring parameters $\beta$ can be fitted to special subgroups. One can then test whether these are statistically significantly different from the parameters fitted for other subgroups. If it is the case that the models can be dis-
tinguished and one can obtain better prediction results with different sets of parameters, it makes sense to apply different model weighting factors or maybe use different model assumptions for scoring different subgroups. For example, consider the two subgroups new drivers and experienced drivers. In contrast to experienced drivers, new drivers have no claim history so their premiums should not be based on the same scoring rules used to set premiums for experienced drivers. However, one can use the interrelation between the claim experience of other young drivers in their first years of driving and the factors used for scoring.

Another concern is data quality and data availability. Lack of data is a problem for any approach, including the one presented here, but an advantage of our approach is that if there is detectable law or a pattern in the data, the model can make good prediction even for groups of cases that had no or few data in the standard tariff class system. Further alternatives include obtaining access to a larger database or using claim data from previous years. Of course, it must be taken into consideration that patterns and dependencies can change over the course of time, but this possibility could be mitigated, at least to some degree, by assigning older data a time-dependent weight that will lowers its influence in determining the scoring model. Changes over time will also make it necessary to recalibrate the risk assessment models at regular intervals. Although data quality and availability can be a problem for our suggested approach, it should be kept in mind that these problems are also found in traditional risk classification methods.

An important issue is the incorporation of claim experience into the prediction model. The actual bonus-malus system adjusts tariffs to past experience by penalizing claims with higher premiums and rewarding time periods without claims by reductions in premiums (see Lemaire/Zi, 1994, p. 287). In other words, if a claim occurs, the insured pays it back, at least partially, by way of a higher premium, which should create an incentive for more careful driving. A possible method for assessing past claim experience and converting it into a bonus or malus for premium calculation is provided by the Bühlmann-Straub-model (see Bühlmann/Straub, 1970). To the degree past claims predict future claims, they should be integrated into the scoring system.

One issue that is very relevant for the development of claim prediction models is the extent to which certain information about insureds can be used without violating laws against discrimination (see, e.g., Stroinski/Currie, 1989, p. 35). For
example, in the German insurance market, basing rates on nationality or ethnic group membership is prohibited by law (see Mayer, 2002, p. 59). Another facet of this issue, mentioned above in the discussion of “insurance scoring” for the U.S. insurance market, is that there is a certain loss in balance effects between the insureds by using additional information as from credit history. On the one hand, due to improved risk assessment capabilities, lower risks will subsidize higher risks a lesser extent. On the other hand, portfolio and risk balance effects are not lost in exchange for an enhanced level of accuracy in risk management, that is, many insureds share the costs of claims. However, a problem could arise if more accurate risk assessment makes automobile insurance unaffordable for a great many people, especially in Germany, where automobile liability insurance is compulsory.

Normally, the relationship between a certain risk factor and the probability of a claim, along with its size, is intuitive. For example, it is not difficult to figure out that the probability of a car accident is larger in a big city than it is in a rural area simply because there are more cars in a big city. Similarly, the expense of a claim under comprehensive insurance coverage for damage to a very expensive car is going to be higher than one made for a cheaper car. However, there are other factors influencing claim probability that are not so easy to measure (see Mayer, 2002, p. 25). Examples include the carefulness of a driver or an affinity for drunk driving. One method for taking this type of factor into account when setting premium rates, and one already in use, is to identify variables that can provide information about the characteristics of the unobservable variables. One such indicator that has long been used for such a purpose is occupation. At a first glance, this information would not seem of much use in assessing automobile insurance risk, but insurers have found that certain occupations are accompanied by either lower or higher risk (see Growitsch et al., 2006, pp. 231–233). The use of credit history, as done in the U.S. market, is another way of gaining information on unobservable factors. An option from the field of statistical data analysis is to create a synthetic or latent variable that measures and evaluates the unobservable characteristics by using a set of observable factors (see, e.g., Loehlin, 2004). A difficulty is that the unobservable factors concern the particular characteristics of one insured person and thus are not useful if more than this individual drives the car. A solution, which, although it does not measure unobservable factors, can help discipline and thus deter risky driving, is the installation of a black box that can
record certain parameters, such as the speed of the car, with the aim of being able to reconstruct the reasons for an accident (see, e.g., Filipova/Welzel, 2005).

Finally, communication is important, too. Customers must be able to understand how their premium rates are derived. In the tariff class system as it stands today, an insured can get a better rate (or, in some cases, a rebate) by, for example, starting to keep his or her car in a garage. Our suggested scoring system would also allow for rate reductions in the event of certain customer action, but the hows and whys of it are not as easy to explain. However, it should be possible to create examples, charts or diagrams that will clearly show the relationships between premiums and risk characteristics so that customers can make informed decisions both about buying insurance and their own behavior.

5. SUMMARY

In this paper, we discussed different methods for risk assessment in the German automobile insurance industry. Currently, automobile insurance risks are classified with respect to different characteristics, leading to several thousand tariff classes, many of which are empty. For these classes, it is difficult to calculate premiums based on observed claim sizes. We suggest an approach to data analysis that focuses more on the functional relationship between the characteristics and the expected claim size and thus avoids fragmenting the data.

To this end, we presented an approach used in the U.S. insurance market called “insurance scoring.” Insurers use weighted information from the insured’s credit history together with other characteristics for an improved risk assessment. We found that two aspects of this method could be very useful to the German automobile insurance market. One involves the use of score values, a method already in practice in the credit industry, which can be derived, e.g., from regression analysis. The second involves the use of deriving information on unobservable factors by taking a look at observable factors, in particular, an applicant’s credit history can provide useful information on the general prudence and reliability of the applicant, factors not easily observed in the normal insurer-insured relationship, but, of course, quite critical to it, especially from the insurer’s point of view.
We demonstrated and discussed ways of calculating the expected claim size of a particular risk in automobile insurance. The expected claim size can be reduced to a certain point score and then be related to a certain level of risk. Obviously, different risk factor combinations can lead to the same level of risk. By applying this technique, searching for tariff classes with similar risk levels as done, e.g., by cluster analysis, becomes unnecessary. The main difference is not a methodical one as classification methods are, to some extent, comparable, but a conceptual one as this approach can reduce the complexity of actual applied risk assessment methods and deliver less-biased predictions because it uses the entire data set in the determination of the scoring model. We thus suggest using the scoring method to set premium prices. However, even though the scoring approach seems to be a very promising alternative for automobile rate making in the German market, further research is needed to verify the benefits of this method for real-world automobile insurance data.

Further, we discussed advantages and disadvantages of the proposed scoring methods, as well as the issue of unobservable factors. These factors have a large influence on the risk level but are not measurable. Therefore, indications need to be gleaned from other information sources as it is done, e.g., by the creation of latent variables.

Adequately assessing the size of risk is crucial to the insurance industry—profitability depends on it. Therefore, we expect that there will be ongoing efforts to improve risk assessment methods, as well as attempts to better retrieve indications for unobservable factors.
REFERENCES


