EMPIRICAL BAYESIAN CREDIBILITY FOR WORKERS' COMPENSATION CLASSIFICATION RATEMAKING

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Abstract

This paper demonstrates how a company can derive accurate classification relativities. The method uses an empirical Bayesian credibility formula as taken from the paper "Credibility for Loss Ratios" by Buhlmann and Straub and modified by the ISO Credibility Subcommittee.

The data required for this method can be purchased from the National Council. A classification review is performed on three years of live data. Relativities predicted by both this method and the present ratemaking formula are compared with the actual relativities from a fourth year of data.

1. INTRODUCTION

Workers' Compensation has traditionally been a highly regulated line of insurance. Rates are usually recommended by the National Council on Compensation Insurance and, with regulatory approval, become the industrywide standard. While many states permit deviations, insurers have generally adhered to the standard rates. Insurers compete on price by offering various dividend plans.

With the creation of the model law for competitive rating in Workers' Compensation, this is rapidly changing. In order to promote a better business climate, many states have passed competitive rating laws.

Under a uniform pricing system, it is not necessary to have rates equal to the expected cost of writing the policy. But in a competitive environment, many economists, such as Paul Samuelson [1], assert that the price will be equal to the expected cost of writing the policy. While the present ratemaking formula, which is described by Kallop [2], makes no systematic deviation from expected cost pricing (on an underwriting basis), it is not obvious that these rates are the best estimates of the expected cost. The present ratemaking method has held up for a long time under a system of uniform ratemaking, but it remains to be seen how long it will hold up under the increased pressure of open competition.

In most states, all insurers report their experience to the National Council. This reporting takes two forms. First, insurers report their aggregate premium and loss experience. Since rates are uniform, it is not necessary to adjust premiums to a common rate level. Thus it is easier to estimate the overall needed rate change with this data. Second, insurers report loss and exposure experience for each insured on a policy year basis. While this data is not as timely as the financial aggregate data, it is more detailed. Because of its fine breakdown, it can be used for deriving class relativities.

The broad-based experience reported for Workers' Compensation should be compared to the experience reported for other lines. In private passenger automobile insurance, for example, many policies are written by independent insurers who do not report their experience. Many different classification systems and rating plans are used. Thus, combining experience is difficult, if not impossible. Because of this, it is difficult for many insurers to set accurate rates.

It can be argued that reporting experience on a standard basis can enhance competition by making it easier for insurers to enter the market. But the need to report experience on a standard basis can discourage insurers from trying innovative classification systems and rating plans. Clearly, some compromises must be made in order to obtain the greatest benefits from competitive rating.

To summarize, the economic incentive to calculate accurate rates for Workers' Compensation is stronger than ever before, and the volume and quality of data are better than in any other line of insurance. Also, methods of data processing are becoming cheaper and more flexible. Under these conditions, improvements in the accuracy of ratemaking can surely be made.

This paper addresses the problem of determining accurate classification relativities. The method used to derive classification relativities differs from the present method in its use of an empirical Bayesian credibility formula.

We begin with a description of the empirical Bayesian credibility formula. We then compare the accuracy of the classification relativities predicted using this formula with those predicted by the present ratemaking formula.

The theory described in this paper is applicable to both loss ratio and pure premium ratemaking. However, it makes no sense to credibility weight the pure premium of a class with a thirty cent rate with the pure premium of a class with a thirty dollar rate. This is frequently the case in Workers' Compensation. Thus, we describe the theory in terms of loss ratios.

The loss ratios are based on Unit Statistical Plan data. Since the overall rate change is determined externally (the National Council uses financial aggregates), these loss ratios are used to determine class relativities.

2. INFORMATION AND ESTIMATION

A general principle in statistical estimation theory is that more information about a certain quantity leads to a better estimate of that quantity. A goal of statistical estimation theory is to develop ways of using all sources of relevant information in arriving at an estimate. In this section we shall show how this principle applies to Bayesian estimation and credibility theory.

Our problem is to estimate the loss ratio for a class of insureds. We consider two sources of information that can be used to estimate the loss ratio.

First, we can use the historical loss ratios for the class. While this information has a direct relationship to the quantity being estimated, it can be subject to random fluctuation because of small volume.

Second, we can use the loss ratio for a group of similar classes. Because of the greater volume of experience, this information has less random fluctuation. However, it has a less direct relationship to the quantity being estimated. The classes in the group may simply have different loss ratios.

Each of these sources of information is relevant to the quantity being estimated. The problem we want to address becomes the following: how can one use both sources of information to derive an estimate of the loss ratio for a class?

We seek a mathematical solution to this problem. To solve this problem we must first specify a model that we feel resembles the situation. We must then specify the information that we have available. We then mathematically derive the best estimate of the loss ratio.

We begin by making the following assumptions.

1. The expected loss ratio, μ, is randomly selected from a distribution with mean M and variance τ^2.
2. Each loss ratio, X, is randomly selected from a distribution with mean μ, and variance σ^2.

This model bears a fair resemblance to our situation. We observe a class loss ratio, X, which fluctuates around the class's expected loss ratio, μ. Our second source of information is the loss ratio, M, for a group of classes. The possibility that classes in this group may have different loss ratios is represented by selecting μ at random from a specified distribution.

The problem is to estimate the true loss ratio for a given class. We now describe some solutions to this problem.

The Bayesian Solution

The Bayesian solution to this problem is to calculate the average μ for all classes with observed loss ratio X. We write this as $\mathrm{E}[\mu|X]$. One must have a complete description of the distributions for X and μ to perform this calculation. For example, if we know that X and μ are normally distributed, it is demonstrated by Hoel [3] that

$$\mathrm{E}[\mu|X] = \frac{\tau^2}{\tau^2 + \sigma^2} \cdot X + \frac{\sigma^2}{\tau^2 + \sigma^2} \cdot M.$$

Hewitt [4] and Mayerson [5] give the Bayesian solution for other distributional assumptions.

It should be noted that the Bayesian solution given above is a linear function of the observed loss ratio, X. While this is also true for many other Bayesian solutions, it is not true for all Bayesian solutions. Hewitt [6] gives an example where the Bayesian solution is not linear.

The Credibility Solution

The credibility solution, given by Buhlmann [7], is to use the linear approximation to the Bayesian solution which minimizes the expected squared error. As noted above, in many cases the credibility solution is identical to the Bayesian solution. While the credibility solution may not be as accurate as the Bayesian solution, it does not require as much information. One need not have a complete description of the distribution of X and μ. One need only have the values of M, τ^2 and σ^2. We will denote the credibility solution by $\mathrm{C}[\mu|X]$.

The credibility solution can be stated as follows. Let

$$\mathrm{C}[\mu|X] = A \cdot X + B.$$

We want to choose A and B so that

$$\mathrm{E}[(\mathrm{C}[\mu|X] - \mathrm{E}[\mu|X])^2]$$

is minimized. The solution can be written in the following form.

$$\mathrm{C}[\mu|X] = \frac{\tau^2}{\tau^2 + \sigma^2} \cdot X + \frac{\sigma^2}{\tau^2 + \sigma^2} \cdot M.$$

Define the credibility factor, Z, as follows:

$$Z = \frac{\tau^2}{\tau^2 + \sigma^2}$$

The credibility solution now takes the more familiar form:

$$C[\mu|X] = Z \cdot X + (1 - Z) \cdot M.$$

The credibility factor can be viewed as a measure which compares the variance of X with the variance of μ. A credibility factor close to zero indicates that the random fluctuations of individual class loss ratios are large compared to the true differences in loss ratios between classes in the group. A credibility factor close to one indicates just the opposite. Philbrick [8] discusses this aspect of credibility theory in detail.

A major problem with the credibility solution is that, in real life situations, one does not know M, τ^2 or σ^2. While it is possible to choose the unknown parameters by judgment, American actuaries have used a more direct approach; they choose the entire estimation formula by judgment. These formulas are generally referred to as the "classical" credibility formulas. The rationale for these formulas is given by Longley-Cook [9].

While the Bayesian and the credibility solutions provide considerable insight into the estimation process, one more step is needed. We must be able to form our estimates entirely from observations. This is the essence of the empirical Bayesian solution.

3. EMPIRICAL BAYESIAN CREDIBILITY

We begin our discussion of empirical Bayesian credibility with a description of the solution given by Buhlmann and Straub [10] in their landmark paper "Credibility for Loss Ratios." This solution has been amplified and modified by the Credibility Subcommittee of Insurance Services Office. Much of the following development is taken from a report written by the Credibility Subcommittee [11].

We begin by specifying the model underlying the empirical Bayesian credibility formula. Next, we give the credibility formula in terms of the parameters of the model. Finally, we show how to estimate the parameters of the model.

The Model

The formula requires the following data.

1. T years of experience for N classes.
2. The premium for class i in year t (denoted by P_{it}).
3. The loss ratio for class i in year t (denoted by X_{it}).

We make the following assumptions.

1. The expected loss ratio for class i, μ_i, is randomly selected from a distribution with mean M and variance τ^2.
2. Each loss ratio, X_{it}, is randomly selected from a distribution with mean μ_i and variance V_i^2/P_{it}.

Most actuaries would agree that the variability of a class loss ratio decreases as the size of the class increases. The assumption that the variance of the loss ratio is inversely proportional to the premium (i.e., $\text{Var}[X_{it}] = V_i^2/P_{it}$) is a simple way to approximate this relationship. Note that the constant of proportionality, V_i^2, can be different for each class.

It is unlikely that this relationship is precise. Meyers and Schenker [12] propose a model of the loss process in which the variance of the loss ratio is not inversely proportional to the premium. In this model the variance of the loss ratio can be written in the form $\text{Var}[X_{it}] = \alpha/P_{it} + \beta$. The constant term, β, is positive when there are additional, but unidentified, sources of variation. Examples of this could include changing economic conditions, or increased emphasis on loss control. Meyers [13] discusses how a positive constant term affects the credibility formula.

The Credibility Formula

For a given class, j, we want to find an estimate, $\hat{\mu}_j$, of the expected loss ratio, μ_j. Here, we present the formula given by Buhlmann and Straub [14].

The estimate is of the following form.

$$\hat{\mu}_j = \sum_i \sum_t A_{it} \cdot X_{it}$$

A_{it} is chosen to minimize $E[(\hat{\mu}_j - \mu_j)^2]$, subject to the constraint that $E[\hat{\mu}_j] = M$.

Note that all the observed loss ratios, X_{it}, contain some information about the expected loss ratio μ_j. The exact nature of this information is specified by the assumptions listed above and the accompanying mathematics. It should be noted that since the X_{jt}'s contain more information about μ_j than the other X_{it}'s, the A_{it}'s depend upon j.

Using the method of Lagrange multipliers, one can solve for the A_{it}'s. Buhlmann and Straub went one step further by algebraically manipulating the solution so as to express it in a form which resembles a standard credibility formula.

Let $P_{i.} = \sum_t P_{it}$ (total class premium),

$$\bar{X}_{i.} = \sum_t P_{it} \cdot X_{it}/P_{i.} \quad \text{(premium weighted average of } X_{it}\text{)},$$

$\Sigma^2 = \mathrm{E}[V_i^2]$

$K = \Sigma^2/\tau^2$ (credibility constant),

$Z_i = P_{i.}/(P_{i.} + K)$ (credibility factor), and

$$\hat{M} = \sum_i Z_i \cdot \bar{X}_{i.} \Big/ \sum_i Z_i \quad \text{(credibility weighted average of } \bar{X}_{i.}\text{)}.$$

Then $\mu_j = Z_j \cdot \bar{X}_{j.} + (1 - Z_j) \cdot \hat{M}$.

There is one point that should not be overlooked. The complement of credibility is assigned to the *credibility-weighted* average loss ratio and not the premium-weighted average loss ratio as many would assume. The reason for this is simply that it is the solution to the minimization problem. It should be noted that $\hat{M}$ has some very nice properties.

First, it can be demonstrated [15] that

$$\sum_i \sum_t P_{it} \cdot \hat{\mu}_i = \sum_i \sum_t P_{it} \cdot X_{it}.$$

This means that the estimates of the class loss ratios are "in balance" with the overall loss ratio.

Second, it can be demonstrated [16] that $\hat{M}$ is the minimum variance unbiased estimate of M.

Estimating the Parameters

The following estimators of Σ^2 and τ^2 were derived by Buhlmann and Straub [17].

Let $P_{..} = \sum_i \sum_t P_{it}$ (total premium),

$$P2 = \sum_i P_{i.}^2 ,$$

$\bar{X}_{..} = \sum_i \sum_t P_{it} \cdot X_{it}/P_{..}$ (premium-weighted average of X_{it}), and

$$W = \sum_i P_{i.} \cdot (\bar{X}_{i.} - \bar{X}_{..})^2/(N - 1)$$

Then estimates for Σ^2 and τ^2 are given by

$$\hat{\Sigma}^2 = \frac{\sum_i \sum_t P_{it} \cdot (X_{it} - \bar{X}_{i.})^2}{\mathrm{N} \cdot \mathrm{T} - \mathrm{N}} \quad \text{and}$$

$$\hat{\tau}^2 = \frac{(W - \hat{\Sigma}^2) \cdot (N - 1) \cdot P_{..}}{P_{..}^2 - P2} .$$

Buhlmann and Straub then used $\hat{K} = \hat{\Sigma}^2/\hat{\tau}^2$ as their estimate of the credibility constant. The credibility of a class loss ratio becomes the following:

$$\hat{Z}_i^1 = \frac{P_{i.}}{P_{i.} + \hat{K}} .$$

The ISO Credibility Subcommittee modified this formula for the following reason. Even though $\hat{\Sigma}^2$ is an unbiased estimate of Σ^2, and $\hat{\tau}^2$ is an unbiased estimate of τ^2, it turns out that $\hat{Z}_i^1$ is a biased estimate of $Z_{i.}$ The modified formula, which attempts to correct for this bias, can be written as follows.

$$\hat{Z}_i = \frac{P_{i.}}{P_{i.} + \hat{K}} \cdot \frac{N - 3}{N} + \frac{3}{N}$$

This modification is identical to that given by Morris and Van Slyke [18]. A derivation of this modification is given by ISO [19]. This derivation makes a number of simplifying assumptions in addition to those already stated. They are as follows.

1. X_{it} is normally distributed.
2. μ_i is normally distributed.
3. Σ^2 is known.

Since these assumptions are somewhat restrictive, this correction for bias should be regarded as only approximate.

Under the above assumptions, it is not possible to correct for this bias when $N < 3$. Thus, one should not use this empirical Bayesian formula when there are three or fewer classes.

Note that the minimum credibility that is possible in this formula is $3/N$.

It is possible for the estimate, $\hat{\tau}^2$, to be negative. This can be disconcerting to those who think that estimates of a variance should be positive. However, this phenomenon does have a natural interpretation. If we assume that the X_{it}'s are normally distributed in addition to our stated assumptions, it is possible to test the hypothesis that all the μ_i's are equal. This test is referred to as analysis of variance (ANOVA), and is described by Freund and Littell [20]. This test calculates a statistic called the F statistic. Abnormally high values of the F statistic indicate that we should reject the hypothesis that all μ_i's are equal, while lower F values indicate failure to reject this hypothesis.

It turns out in our case that $F = W/\hat{\Sigma}^2$. Thus we have that $\hat{\tau}^2$ is negative if and only if F is less than one. Since under the null hypothesis, $E[F] = (N \cdot T - N)/(N \cdot T - N - 2) > 1$, a negative $\hat{\tau}^2$ indicates failure to reject the hypothesis that all μ_i's are equal.

Thus, we should assign a credibility of zero when $\hat{\tau}^2$ is negative.

One additional point should be made. The derivation of these estimators requires that the loss ratios for a given class are independent from one year to the next. Most ratemaking procedures in use at this time use loss ratios at "present rates." If rates are revised yearly, all but the most recent year of experience is used in calculating the present rate. The premium, and hence the loss ratio, for the most recent year will be influenced by the experience of the prior years. Thus, the independence assumption is violated!

The effect of using premium at present rates is to understate our estimate of τ^2. W is sharply reduced, while $\hat{\Sigma}^2$ will not be significantly affected. An extreme case results when all years of the current review were used in making the present rates, and a credibility of one was used. In this case, all the X_{it}'s are equal to the expected loss ratio, W is equal to zero and $\hat{\tau}^2$ is negative.

What to do about this problem is currently being debated by the Credibility Subcommittee. Some members feel that present rates should be used for estimating loss ratios, and the focus of the debate is on how to do this. In this paper we do not use present rates. Instead we use the most recent rates which were not based on the current experience.

It should be noted that if X_{it} is a pure premium rather than a loss ratio, the X_{it}'s will be independent, and it is not necessary to refer to older rates.

In summary, we have presented a credibility formula whose parameters are derived entirely from available data, and we have stated the assumptions that are used in deriving this formula. As is often the case in actuarial science, the model associated with these assumptions is necessarily simpler than the real world. However, this formula is easy to use and can produce accurate results, as we shall now demonstrate.

4. RATEMAKING WITH EMPIRICAL BAYESIAN CREDIBILITY

We now demonstrate how to use empirical Bayesian credibility in classification ratemaking.

The Data

Whenever the National Council files rates, it releases the raw data that underlie the rates. Recently, they began selling tapes containing loss and exposure data (Schedule Z), by class, derived from the Unit Statistical Plan. For this study, we obtained the tapes which correspond to the 1982 and 1983 rates for the state of Michigan.

The most recent rates which did not utilize any of the above data were those for the year 1979. Thus we calculate the premium by multiplying the payroll times the 1979 rate.

Below, we use the data on the first tape to calculate class relativities. Thus it is possible to make a direct comparison between the 1982 rates and the rates produced below. The tape which corresponds to the 1983 Michigan rates contained an additional year of data. We will use this additional year of data to compare the accuracy of the rates derived using the present ratemaking formula with those derived using empirical Bayesian credibility.

The losses were adjusted for law changes and loss development with factors taken from the 1982 Michigan rate filing. One technical point should be made here. The 1982 National Council rates do not reflect the modification due to (Michigan) Senate Bill 1044. This is appropriate since none of the experience reflects this bill and the adjustment was made outside the usual ratemaking formula.

Our purpose is to provide a direct comparison of ratemaking formulas, and so classes which presented special problems were deleted from this analysis. The special problems were of two kinds. First, many classes were absorbed into other classes between 1979 and 1982. It was felt that the 1979 rate for the new class could not be accurately estimated. Second, some classes contained disease elements which require special treatment. In practice, these problems must be dealt with. But that is beyond the scope of this paper.

Exhibit I shows the data used.

Determining the Class Loss Ratios

The empirical Bayesian credibility formula was applied to the data of Exhibit I with the following results.

$$
\begin{aligned}
N &= 319 \\
\hat{\Sigma}^2 &= 92374 \\
\hat{\tau}^2 &= 0.019237 \\
\hat{K} &= 4801900 \\
\hat{M} &= 0.5822
\end{aligned}
$$

For each class i, the credibilities, $\hat{Z}_i$, and the estimates, $\hat{\mu}_i$, are given in Exhibit I.

Distributing the Overall Rate Change

Even a moderately large insurer is unlikely to have exposure in all classes for which it must have a rate. Thus most insurers must obtain data similar to that described above in order to make independent rates for all classes. However, a company does not need data in such fine detail to determine the overall rate change.

As noted above, the National Council uses financial aggregate premium and loss experience to determine the overall rate change. Individual companies operating in a competitive environment invariably will have their own way of deriving the overall rate level. It is not our purpose to describe methods of determining the overall rate change. Instead we will describe how a company might distribute the overall rate change to the individual classes.

The procedure described below will produce estimates, $\hat{\mu}_i$, of the loss ratio at 1979 rates for each class i. Since it is quite likely that an insurer's payroll in the various classes will have changed since 1979, a logical procedure for determining the final rates might proceed as follows.

Let L = Total loss provision for the insurer's current book of business at the proposed rate level,
E_i = insurer's current payroll for class i and
R_i = 1979 rate for class i.

We define the rate adjustment factor, A, as follows.

$$A = L \Big/ \left(\sum_i E_i \cdot R_i \cdot \hat{\mu}_i \right)$$

The loss provision in the rate for class i is then given by the expression $R_i \cdot \hat{\mu}_i \cdot A$. If the loss provision in the rate for class i is defined in this manner, the total loss provision for the new class rates on the current book of business will be equal to L.

It should be noted that the estimates, $\hat{\mu}_i$, are really being used to determine class relativities.

5. TESTING CREDIBILITY FORMULAS

We shall now compare the accuracy of the rates produced by the empirical Bayesian credibility formula with those rates produced by the present ratemaking method.

The Underwriting Test

The accuracy of a ratemaking method can have a very important practical consequence. Suppose you are in an environment where some less accurate ratemaking method is being used. If you choose, or are required, to use the less accurate rates, you can use the more accurate rates to identify the better insureds. By writing these better insureds, you will have better than average underwriting results. Conversely, suppose you are able to use the rates indicated by the more accurate ratemaking method. You would then be charging a lower rate for the better insureds, and a higher rate for the worse insureds. You could then increase your writings for the better insureds and still make an adequate profit, while your competitors who use the other ratemaking method should write more of the worse insureds and make a less than adequate profit. A common phrase for this procedure is "skimming the cream."

Our first test will be based on this phenomenon, and will appropriately be called the "Underwriting Test." This test proceeds as follows. We first estimate the expected losses predicted by each formula for the test year. For each class, i, the expected losses are computed as follows.

Present Method:

$$Expected\ Loss_i = Payroll_i \cdot 1982\ Rate_i \cdot 0.769384$$

Empirical Bayesian Credibility:

$$Expected\ Loss_i = Payroll_i \cdot 1979\ Rate_i \cdot \hat{\mu}_i \cdot 1.053661$$

Since we are interested only in class relativities, we use the factors 0.769384 and 1.053661 to force the expected loss to sum to the total expected losses for the test year.

Next, we divide the classes into two groups. Group 1 consists of all classes for which the present ratemaking formula gives lower expected losses. Group 2 consists of all other classes.

For each group we then compare the ratio of actual losses for the test year to the expected losses predicted by both ratemaking formulas. The results are in the following table.

TABLE 1

UNDERWRITING TEST

	Group 1	Group 2	Total
1. # Classes	162	157	319
2. Actual Loss	216906003	199032667	415938670
3. Exp. Loss (Pres. Mthd.)	208238132	207700538	415938670
4. Exp. Loss (E. B. Cred.)	220310030	195628640	415938670
5. (2)/(3)	1.042	0.958	1.000
6. (2)/(4)	0.985	1.017	1.000

Line 5 of Table 1 shows that by using the present ratemaking formula and underwriting in favor of the Group 2 classes, one expects a better than average profit. Line 6 of Table 1 shows that by using the rates produced by the empirical Bayesian credibility formula, one could charge less than the rates produced by the present formula for the Group 2 classes and still make an average profit. Competitors with the same overall rate level who use the present ratemaking formula may end up writing a greater concentration of Group 1 classes and make less than their anticipated profit.

Thus we conclude that the empirical Bayesian credibility formula produced more accurate rates for this data.

We now address the statistical significance of this result. Our test is similar to the "bootstrap" technique described by Diaconis and Efron [21]. For our test, we constructed 2000 groups of insureds in which the members of the group were selected at random with a probability of 0.5. The loss ratios for each group were calculated and then listed by percentiles. These percentiles are given in Table 2.

TABLE 2

RANDOM LOSS RATIOS—
PRESENT RATEMAKING
METHOD

Percentile	Loss Ratio
.010	.939
.025	.949
.050	.957
.100	.965
.150	.971
.200	.976
.250	.980
.750	1.021
.800	1.027
.850	1.033
.900	1.041
.950	1.053
.975	1.064
.990	1.075

Looking at Table 2 we see that the Group 1 loss ratio for the present ratemaking method of 1.042 is near the 90^{th} percentile of the random loss ratio distribution. Similarly, we see that the Group 2 loss ratio of .958 for the present ratemaking method is close to the fifth percentile of the random loss ratio distribution.

Now there are two types of errors that can be made. A Type I error occurs when one keeps the present method when the empirical Bayesian method is better. A Type II error occurs when one changes from the present method to the empirical Bayesian method when the two methods are equally accurate. Table 2 shows that the probability of making a Type II error is less than one in ten. The probability of making a Type II error (i.e. the significance level) that should be required in order to change methods depends upon the relative costs of the two types of errors.

A single insurance company operating in a competitive environment may miss a good opportunity to expand in some profitable classes if it makes a Type I error, but should lose very little by committing a Type II error. A one in ten chance of making a Type II error should be sufficient to justify adopting the empirical Bayesian method.

A Type II error can be very costly for a rating bureau which is making an industrywide filing in a noncompetitive environment. Should the error be discovered after such a filing, the cost of returning to the present method can be enormous in time, money, and embarrassment. In such cases a one in ten chance of making a Type II error may not be sufficient to justify changing methods, and additional tests should be made. However, it should be noted that the cost of a Type I error is not insignificant. Companies can use the empirical Bayesian method for underwriting. There could be availability problems for some classes.

The table of loss ratio distributions for the empirical Bayesian credibility formula is similar to Table 2. The loss ratios of .985 for Group 1 and 1.017 for Group 2 are well within the normal range of fluctuation.

Mean Squared Error

A natural test for a ratemaking method is to measure how close the expected loss comes to the actual loss for the next year. With this in mind we calculate the following statistic.

$$MSE = \sum_i P_i \cdot (A_i/E_i - 1)^2/N$$

Where A_i = actual loss for class i
E_i = expected loss for class i
P_i = 1979 rate for class i times the payroll for class i
N = number of classes (319).

We shall refer to the number $P_i \cdot (A_i/E_i - 1)^2$ as the squared error for class i and we shall refer to MSE as the mean squared error.

The test statistics for the ratemaking methods considered above are given in the following table.

TABLE 3

	$\underline{MSE}$
Empirical Bayesian Credibility	289651
Present Ratemaking Formula	298063

Here we see that the empirical Bayesian credibility formula produces the lower mean squared error.

To test if the differences between these mean squared errors are statistically significant we must consider the following.

1. The squared error for a class using one method is not independent of the squared error for the same class using another method.
2. The distribution of the squared errors is not normal.

A test that can work under these conditions is the Wilcoxon signed ranks test [22], which we now describe.

For a class i, let $SE1_i$ be the squared error for the present ratemaking method and let $SE2_i$ be the squared error for empirical Bayesian credibility. Let

$$DSE_i = SE1_i - SE2_i$$
$$R_i = \text{Rank}(|DSE_i|) \cdot \text{Sign}(DSE_i)$$
$$T = \sum_i R_i \bigg/ \left(\text{Square root}\left(\sum_i R_i^2\right)\right)$$

We want to test the hypothesis

H_0: $\text{E}[SE1_i] = \text{E}[SE2_i]$

against the alternative hypothesis

H_1: $\text{E}[SE1_i] \neq \text{E}[SE2_i]$.

For large N, we reject H_0 at the level of significance α if T lies below the $(\alpha/2)^{\text{th}}$ or above the $(1 - \alpha/2)^{\text{th}}$ percentile of the standard normal curve.

When comparing the MSE of the rates produced by the empirical Bayesian credibility formula with those produced by the present formula, we get

T = .198 which is at the 56[th] percentile of the standard normal distribution. Thus we cannot reject H_0. Thus we conclude the expected mean squared errors are not significantly different.

Of the two tests conducted, the author considers the underwriting test to be the most relevant, since it corresponds directly to actions an insurance company can take. However the mean squared error test corresponds more closely to the criteria under which the empirical Bayesian credibility formula was derived, with the main difference being the substitution of actual loss ratios for "true" (but unmeasurable) loss ratios. This substitution adds a great deal of volatility to the test.

6. CONCLUSION

This paper describes how an empirical Bayesian credibility formula can be used to determine class relativities for Workers' Compensation insurance. Tests which compared the accuracy of this method with the present ratemaking method showed that the empirical Bayesian credibility formula produced more accurate rates.

The level of significance of these tests was sufficient for use by individual companies in a competitive environment, but the author would stop short of recommending industrywide use of this method in a highly-regulated noncompetitive environment until further tests are made.

However, it should be pointed out that if the empirical Bayesian approach is even marginally more accurate than the present approach, its accuracy should increase over time. One of the features of the approach described above is that it had to use the 1979 rates which were derived by the present ratemaking formula. If this method were adopted for the 1985 rates, the rates calculated above could be used in place of the 1979 rates. Gradually, the rates will become even more accurate.

Another advantage to the empirical Bayesian approach is that it calculates an optimal result based on an explicit set of assumptions. By knowing how well the assumptions are met, one can better decide when to adjust the calculated results on a judgemental basis, or when to derive a new formula based on alternative assumptions.

This author doubts that the above approach will be the last word in credibility theory, but it is hoped that this paper has set a standard that proposals for alternative formulas will follow. This standard is that the predictions should be tested on independent data. This standard is part of the scientific method and should be applied to actuarial science.

7. ACKNOWLEDGMENTS

The ratemaking method described in this paper is being used by my company. In developing this method I worked very closely with Burt Covitz. Burt's very detailed knowledge of Workers' Compensation ratemaking made this method much better than it might otherwise have been. Brad Alpert and Mike Kooken also contributed many valuable comments.

I have also profited tremendously by the very thorough work done by the staff of the ISO Credibility Subcommittee. ISO deserves to be commended for the resources committed to this subcommittee.

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9. NOTES ON EXHIBIT I

Exhibit I—Individual Classification Data and Results
List of Variables

CLASS	— NCCI class code
*PI*1	— Policy year starting 4/78 payroll times *RATE*79
*PI*2	— Policy year starting 4/77 payroll times *RATE*79
*PI*3	— Policy year starting 4/76 payroll times *RATE*79
*XI*1	— Policy year starting 4/78 loss developed from first report to ultimate divided by *PI*1
*XI*2	— Policy year starting 4/77 loss developed from second report to ultimate divided by *PI*2
*XI*3	— Policy year starting 4/76 loss developed from third report to ultimate divided by *PI*3
*RATE*79	— NCCI rate in effect for 1979
*RATE*82	— NCCI rate in effect for 1982 (Before S.B. 1044)
PAYROLL	— Payroll for policy year starting 4/79
ACTLOSS	— Policy year starting 4/79 loss
PI	— $P_{i.}$
XI	— $\bar{X}_{i.}$
ZI	— $\bar{Z}_i$ (credibility for class *i*)
UI	— $\hat{\mu}_i$ (credibility estimate for class *i*)
ELOSS	— Expected loss for policy year starting 4/79 predicted using *UI* (= *RATE*79**PAYROLL***UI**1.053661)
NCCIELOS	— Expected loss for policy year starting 4/79 predicted using NCCI rates (= *RATE*82**PAYROLL**0.769384)

EXHIBIT I

INDIVIDUAL CLASSIFICATION DATA AND RESULTS

CLASS	PI1	PI2	PI3	XI1	XI2	XI3	RATE79	RATE82	PAYROLL	ACTLOSS	PI	XI	ZI	UI	ELOSS	NCCIELOS
5	842937	864503	589346	0.277	0.506	0.144	6.73	3.81	165413	751702	2296787	0.329	0.330	0.499	585077	522010
11	1460127	1387183	1419262	0.674	0.248	0.374	6.73	3.81	297690	1238787	4266572	0.436	0.475	0.512	1081881	913874
34	268738	279120	308060	0.068	0.104	0.295	8.49	5.54	44732	51810	855917	0.161	0.159	0.515	206156	203078
35	1017404	959527	882704	0.253	0.501	0.408	5.57	2.95	230480	1495785	2859635	0.384	0.379	0.507	685882	554811
42	2779440	2437089	2092952	0.249	0.293	0.264	9.21	4.09	316174	1089411	7309481	0.268	0.607	0.391	1200498	1038688
106	1026492	1095728	1055057	0.562	0.376	0.412	15.79	10.96	63261	691857	3177277	0.448	0.404	0.528	555663	544961
128	1344541	1248626	1215192	0.384	0.242	0.469	12.56	6.82	105661	1068326	3808360	0.364	0.448	0.485	677807	571645
129	1653095	1947742	1787954	0.317	0.280	0.749	13.15	7.59	201655	2000139	5388791	0.447	0.533	0.510	1425600	1205471
130	1877080	1810503	1588122	0.941	0.685	1.157	13.38	14.67	169560	2286851	5275704	0.918	0.528	0.760	1815859	1989666
301	444153	375746	349813	0.570	0.072	0.687	8.70	7.26	47141	475465	1169711	0.445	0.203	0.554	239541	255929
908	1008855	995022	928189	0.037	0.070	0.009	53.00	40.00	20021	64676	2932066	0.039	0.385	0.373	417325	626255
909	420680	409890	385515	0.002	0.002	0.000	65.00	37.00	6597	3390	1216085	0.002	0.210	0.460	208075	191071
912	359024	399760	361456	0.198	0.037	0.232	152.00	159.00	2335	2250	1120240	0.152	0.197	0.497	186050	293009
913	1928964	2110020	1962774	0.029	0.061	0.045	138.00	101.00	14418	32915	6001758	0.045	0.560	0.282	590690	1155196
1320	559737	495926	463013	0.381	0.771	0.283	9.45	6.25	67905	881524	1518677	0.478	0.247	0.556	376303	332221
1322	778471	802038	595139	0.367	0.691	0.087	23.39	16.56	56306	671463	2175648	0.410	0.318	0.527	731756	627720
1463	677413	620715	677215	0.244	0.937	0.337	10.81	10.30	51946	188430	1975344	0.494	0.298	0.556	328861	390248
1470	858434	832018	614724	3.191	0.536	0.312	8.81	11.05	24078	26849	2305175	1.465	0.331	0.874	195381	191335
1654	203068	182355	169822	0.040	0.005	0.011	9.00	10.58	24376	133598	555245	0.020	0.112	0.519	120008	199446
1924	737381	792484	721109	0.258	0.426	0.159	9.22	6.75	13834	25908	2250975	0.286	0.326	0.486	65268	70172
1925	4825579	5451995	5318449	0.690	0.688	0.587	9.86	9.13	357602	1975059	15596023	0.654	0.767	0.637	2368092	2509787
2001	271555	222978	287299	1.636	2.840	0.233	5.40	6.44	59402	131157	781832	1.464	0.148	0.713	240927	289443
2002	228466	183177	154383	0.209	0.114	0.361	12.82	7.44	20080	77443	566026	0.219	0.114	0.541	146719	113146
2003	6162653	6825105	6530682	0.512	0.511	0.638	7.63	6.22	854319	5415420	19518440	0.554	0.804	0.559	3841239	3965999
2014	456234	426782	340787	0.246	1.248	0.458	7.59	6.04	70179	209135	1223803	0.654	0.211	0.597	335292	323904
2016	1164795	2808874	2677964	0.377	0.524	0.687	2.89	2.59	400986	505827	6651633	0.564	0.585	0.572	697956	765473
2039	307383	399821	398957	0.262	0.153	2.394	7.35	8.41	40028	26395	1106160	0.991	0.195	0.662	205217	248834
2041	684215	601603	467841	0.854	0.309	0.276	7.23	5.37	89960	231692	1753659	0.513	0.274	0.563	385916	375862
2065	200748	539073	532162	0.314	0.629	0.622	5.20	4.89	180348	445940	1271983	0.576	0.217	0.581	573990	668581
2070	1754005	2006385	2168261	1.701	0.666	0.708	5.99	7.29	349583	1988480	5928651	0.988	0.557	0.808	1782696	1887395
2081	1356370	1589739	1445421	0.594	0.510	0.656	16.11	13.10	82282	646318	4391529	0.584	0.483	0.583	814315	826122
2105	425216	309104	214443	0.235	0.324	0.517	7.27	4.84	58530	584773	948763	0.328	0.173	0.538	241327	219520
2110	880299	912997	772664	0.664	0.472	0.257	9.31	6.54	114640	730328	2565961	0.473	0.354	0.544	611373	579817
2111	2004770	1739229	1595198	0.807	0.830	0.714	8.66	9.35	222884	1848896	5339196	0.787	0.531	0.691	1404842	1654886
2112	225601	145303	242064	0.250	0.518	0.740	7.28	5.63	18799	219716	612968	0.507	0.122	0.573	82639	80874
2121	1616249	1426266	1301183	0.656	1.017	0.331	4.50	4.66	421140	601444	4343697	0.677	0.480	0.628	1253717	1355588
2143	921793	771171	622763	0.277	0.229	0.357	12.14	7.21	63674	294217	2315727	0.283	0.332	0.483	393319	352559
2150	59941	65115	110908	2.141	0.057	0.302	13.89	12.70	4992	4980	235964	0.702	0.056	0.589	43028	48210
2503	8920	8487	8695	0.136	0.025	0.039	0.68	0.73	11547	310	26103	0.068	0.015	0.575	4754	6291
2570	458832	416927	336260	1.811	1.288	1.188	10.25	11.86	29368	207151	1212019	1.458	0.209	0.765	242777	271817
2571	362058	356614	317728	1.484	1.400	2.317	7.68	8.87	38895	197500	1036400	1.710	0.185	0.791	249039	269241
2576	750939	669319	586290	0.641	1.249	0.433	9.79	7.82	48671	315221	2006548	0.783	0.301	0.643	322734	295533
2587	293177	234319	125571	1.483	1.690	0.540	4.18	4.11	66426	104180	653067	1.376	0.128	0.684	200073	212845
2683	83435	13788	44039	6.704	2.081	1.190	3.82	4.52	21216	98762	141262	4.534	0.038	0.731	62447	72916
2688	128785	248631	177659	0.155	0.441	0.451	4.35	2.86	42562	67237	555076	0.378	0.112	0.559	109117	95481
2702	1711439	2173770	2725812	0.372	0.471	0.240	47.85	13.62	26237	466217	6611021	0.350	0.583	0.447	591071	291900
2710	733400	808139	1039931	0.571	0.893	0.662	17.88	15.58	34301	106246	2581470	0.708	0.356	0.627	405254	431960
2731	259750	263581	263538	0.239	0.426	1.004	12.44	9.20	19562	6712	786869	0.558	0.149	0.579	148357	140878
2759	1478929	1572742	1549495	0.881	0.604	0.582	18.68	16.94	47023	383980	4601166	0.686	0.494	0.633	586209	647258
2797	2364423	3755144	2970229	0.505	0.420	0.499	11.12	7.47	119425	348353	9089797	0.468	0.658	0.507	709838	684408
2802	4805556	4841774	4342353	0.426	0.540	0.461	11.36	7.54	353227	1754127	13989682	0.477	0.747	0.503	2128660	2091224
2841	565878	731875	697613	1.723	0.416	0.509	10.12	9.12	56100	490748	1995366	0.819	0.300	0.653	390900	400907
2913	13284	110105	11821	0.000	0.095	0.000	5.16	4.09	23433	20017	135210	0.077	0.037	0.564	71827	73600
2923	678226	723997	721849	0.270	0.699	0.294	6.78	4.07	103876	334844	2124073	0.425	0.313	0.533	395420	319253
3004	1633796	1551150	1418600	0.566	0.422	0.090	5.45	3.90	309797	607108	4603546	0.371	0.494	0.478	849970	811255
3018	3288549	3031377	2628498	0.527	0.563	0.913	4.56	4.97	565089	1430447	8948423	0.653	0.654	0.628	1705781	1991793

EXHIBIT I (continued)

CLASS	PI1	PI2	PI3	XI1	XI2	XI3	RATE79	RATE82	PAYROLL	ACTLOSS	PI	XI	ZI	UI	ELOSS	NCCIELOS
3022	1540151	2449373	2055905	0.468	0.569	0.462	6.59	5.02	196702	248557	6045429	0.507	0.562	0.540	737551	725022
3027	794876	726565	1040278	0.751	1.720	0.619	6.39	4.97	114822	683576	2561718	0.972	0.354	0.720	556962	413873
3028	2117047	1836704	1695235	0.558	0.443	0.312	8.58	5.85	237855	571219	5648987	0.447	0.545	0.508	1093306	1030513
3030	3808876	3502056	3047891	0.477	0.523	0.799	16.08	13.10	197446	1932284	10358823	0.587	0.686	0.586	1959711	1858365
3064	155612	117603	130249	0.046	0.438	0.397	6.53	5.70	27554	38378	403464	0.274	0.086	0.556	105336	119302
3096	6984920	6725930	5413338	0.264	0.382	0.384	4.50	3.34	1795443	2849911	19124188	0.339	0.801	0.388	3299958	4501892
3110	3480299	3314510	3455698	0.545	0.762	0.616	15.80	16.15	201877	1421137	10250508	0.639	0.684	0.621	2088024	2252031
3111	452491	491198	660913	0.330	0.513	0.281	8.77	6.10	40034	461273	1604602	0.366	0.258	0.526	194757	182973
3114	442374	385490	438817	0.510	1.328	0.853	6.26	5.80	64350	42533	1266682	0.878	0.216	0.646	274248	281563
3116	6884538	6243554	5414449	0.519	0.714	0.585	4.50	3.34	1668460	2312161	18542541	0.604	0.796	0.599	4742654	4076124
3122	53374	168605	170861	0.590	0.459	0.097	5.54	4.45	22228	280460	392840	0.319	0.084	0.560	72671	75736
3131	1541606	1344256	1102200	0.820	0.641	0.946	7.23	7.39	192501	773025	3988062	0.794	0.459	0.680	996703	1099051
3132	5503567	5162026	4652120	0.295	0.473	0.279	9.45	4.90	495875	1499001	15317714	0.350	0.764	0.405	1999959	1799508
3146	10461448	10327501	10341663	0.642	0.575	0.598	6.34	5.44	1361354	5466606	31130611	0.605	0.868	0.602	5477101	5744591
3169	1263320	1103556	997050	0.784	0.818	0.167	8.63	6.95	162918	347298	3363925	0.612	0.418	0.595	881064	872144
3180	71111	52971	67226	1.084	0.766	0.570	5.78	5.83	9806	69270	191308	0.815	0.047	0.593	35430	44346
3188	1342651	2262766	2900956	0.250	0.467	0.630	12.23	8.68	94382	511048	6506374	0.495	0.579	0.532	646523	628503
3220	120876	116823	105879	0.245	0.003	0.041	4.55	3.91	24435	0	343579	0.100	0.076	0.546	63938	68709
3240	192267	519911	357551	0.577	0.543	1.075	5.71	6.49	29032	402242	1069729	0.727	0.190	0.610	106497	141726
3241	491883	557044	439154	0.520	0.239	0.153	9.85	6.13	51345	128496	1488081	0.306	0.244	0.515	274420	231984
3303	611573	500254	1387789	0.475	0.402	0.293	20.39	11.08	41157	775909	2499615	0.360	0.349	0.505	446256	342341
3306	100529	85929	59749	0.544	0.165	0.382	4.26	3.55	20005	23383	246208	0.372	0.058	0.570	51195	53947
3307	3526603	3389576	3011719	0.421	0.629	0.602	13.21	9.75	202341	1676944	9927897	0.547	0.677	0.558	1572891	1485384
3315	933144	905448	797898	0.434	0.796	1.513	3.00	3.70	325871	998596	2636490	0.885	0.361	0.691	712108	881089
3341	3072918	1782323	2073385	0.200	0.413	0.389	10.34	4.78	388072	1725585	6928626	0.311	0.595	0.421	1780030	1384467
3365	5239753	4020307	2634862	0.510	0.349	0.686	11.02	8.28	454320	2961773	11894922	0.495	0.715	0.520	2741949	2710325
3372	7957781	8035243	7368786	0.423	0.464	0.384	18.51	10.86	314904	2146146	23361810	0.425	0.831	0.452	2773853	2718522
3373	668306	713338	613002	0.682	0.424	0.647	29.18	21.72	14098	181411	1994647	0.579	0.300	0.581	251975	232597
3382	209007	140749	123465	1.144	0.332	1.127	3.39	3.06	28162	130	473222	0.898	0.098	0.613	61691	65526
3400	21847307	26284498	24347583	0.649	0.719	0.533	17.29	15.09	933011	8622676	72479387	0.635	0.938	0.632	10743705	11088736
3548	327022	288492	234682	0.513	0.285	0.250	5.84	3.25	63481	43622	850196	0.363	0.158	0.547	213860	157495
3559	370556	417932	1514657	0.780	0.369	0.680	4.24	3.57	88271	197004	2303145	0.640	0.331	0.601	237093	229626
3581	170491	150209	182260	1.426	0.347	0.810	3.47	3.26	47764	348487	502961	0.880	0.103	0.613	107058	117467
3612	4240098	4058378	3560756	0.644	0.349	0.454	4.66	3.43	602505	1992063	11859232	0.486	0.715	0.514	1519364	1507312
3620	2230698	2563176	2861172	0.507	0.288	0.563	17.03	12.03	113088	516514	7655045	0.455	0.618	0.503	1021646	964833
3628	8506844	8354286	7290971	0.450	0.638	0.568	4.72	3.34	2057991	3851358	24152100	0.551	0.836	0.556	5689534	4971061
3634	1022022	1092893	1016138	0.421	0.757	0.835	3.85	3.62	359172	684173	3131053	0.672	0.400	0.618	900969	973238
3635	3681690	2341564	3761357	0.561	0.657	0.535	5.90	4.86	532338	1623707	9784611	0.574	0.674	0.577	1908445	1905057
3638	1174961	1092317	864647	0.937	0.473	0.844	6.93	6.24	174342	982363	3131925	0.750	0.400	0.649	826537	820703
3643	4893011	4897730	3675854	0.877	0.571	0.708	5.80	5.81	660342	1677062	13466595	0.719	0.740	0.684	2758959	2897156
3647	176951	839659	672441	0.497	0.376	0.476	8.67	6.56	62129	506455	1689051	0.429	0.267	0.541	307185	300974
3648	2275335	2298681	2223042	0.974	1.094	0.617	7.15	8.13	158342	1517970	6797058	0.898	0.590	0.768	916691	1021213
3681	2248815	2214605	1804147	1.389	0.761	0.758	5.28	5.19	258808	574970	6267567	0.985	0.570	0.812	1169474	1072183
3685	1153182	1098880	862330	1.363	0.761	0.755	2.18	2.25	634293	995803	3114392	0.982	0.399	0.742	1081091	1073490
3719	214934	38736	127144	0.002	0.009	0.003	9.29	7.23	25039	80410	380814	0.003	0.082	0.535	131034	117753
3724	12702936	12741665	11011225	0.291	0.424	0.412	13.16	6.74	757668	3263651	36455826	0.374	0.885	0.398	4185168	3428900
3726	4343506	5820391	3645102	0.352	0.369	0.377	13.40	8.46	171646	900917	13808999	0.366	0.744	0.421	1020478	928836
3803	1607945	1327867	1034691	0.906	0.614	0.123	7.43	6.58	137	0	3970504	0.604	0.458	0.592	634	682
3807	572970	334702	499360	0.169	0.724	0.604	12.00	8.10	36475	157732	1407031	0.456	0.234	0.553	254858	219443
3808	673987	551242	381031	0.400	0.468	1.364	8.37	6.81	109735	662855	1606260	0.652	0.258	0.600	580905	568775
3821	1497541	1428867	1360542	0.162	0.481	0.312	17.97	8.10	78796	361175	4286950	0.316	0.477	0.455	679299	512118
3824	785816	1746149	1475725	0.449	0.528	0.507	10.88	8.25	49651	281979	4007690	0.505	0.460	0.547	311232	308717
3827	124113	100468	75771	0.045	0.704	0.025	3.44	2.93	42521	20023	300352	0.260	0.068	0.560	86375	88521
4034	4032715	4230401	3987395	0.357	0.482	0.330	16.76	9.39	224591	1291042	12250511	0.392	0.721	0.445	1764200	1573983
4112	1066	12027	9662	0.000	0.136	3.987	2.48	2.02	1992	405	22754	1.765	0.014	0.599	3118	3045
4130	1218479	1214366	1114642	0.464	0.350	0.251	7.41	4.69	179154	909047	3547487	0.358	0.430	0.486	679657	640147

EXHIBIT I (continued)

CLASS	PI1	PI2	PI3	XI1	XI2	XI3	RATE79	RATE82	PAYROLL	ACTLOSS	PI	XI	ZI	UI	ELOSS	NCCIELOS
4131	525750	474279	364110	0.862	0.332	0.473	7.57	6.08	58065	312722	1364139	0.574	0.229	0.580	268779	269233
4150	160788	152437	158834	0.111	0.063	0.146	1.66	1.13	96319	17592	472059	0.107	0.098	0.536	90237	84088
4206	495276	480714	403366	0.446	0.274	0.376	8.24	5.59	39003	0	1379356	0.365	0.230	0.532	180238	164481
4207	341426	398955	231045	0.236	0.700	0.152	7.15	4.73	25708	32668	971425	0.407	0.176	0.551	106782	90405
4240	118122	116680	97614	0.159	0.119	0.118	7.65	4.99	13887	131370	332416	0.133	0.074	0.549	61471	53482
4243	1791218	2280592	2987898	0.715	0.612	0.701	11.16	11.09	131087	1421198	7059708	0.676	0.599	0.638	983892	1089232
4244	3639612	3563932	3331370	0.569	0.756	0.442	13.75	11.94	230048	1307262	10534914	0.592	0.690	0.589	1963423	2074198
4250	355089	480466	700766	0.891	0.833	0.688	4.06	4.26	76089	809733	1536321	0.780	0.250	0.632	205600	240755
4251	586866	535595	452088	0.770	0.648	0.324	5.42	4.46	101807	180679	1574549	0.601	0.254	0.587	341254	349042
4253	161825	327854	509690	0.122	0.196	0.340	2.11	1.28	40715	33254	999369	0.258	0.180	0.524	47415	39162
4273	348897	317658	371601	0.202	0.599	0.317	8.46	5.83	41940	332286	1038156	0.364	0.186	0.542	202563	181608
4279	1814454	2074848	2422609	0.501	0.446	0.679	10.40	8.11	157608	712366	6311910	0.551	0.572	0.564	974977	990492
4304	1469845	1749031	1399756	0.742	0.959	1.407	4.57	5.49	234939	779353	4618632	1.026	0.495	0.802	907101	969235
4307	390753	369029	424123	1.201	1.638	0.726	5.45	5.53	66721	148888	1183905	1.167	0.205	0.702	269083	284486
4308	28684	34037	38308	0.344	2.060	0.359	1.05	0.89	21712	64911	101029	0.928	0.030	0.592	14234	14507
4351	68873	66931	55585	0.186	1.056	0.560	0.60	0.62	113193	273950	191390	0.599	0.047	0.583	41722	53204
4352	23348	21209	16847	0.097	0.190	0.101	1.44	1.68	11018	63676	61404	0.130	0.022	0.572	9568	14243
4360	39198	32830	27486	0.077	0.826	0.023	1.28	1.29	18432	905	99514	0.309	0.030	0.574	14273	17955
4361	687176	628267	600357	0.580	0.983	0.353	1.63	1.29	459255	255888	1915800	0.641	0.292	0.599	472811	469006
4420	4244831	4195915	4021782	0.966	1.373	1.530	12.59	16.38	301827	3854741	12462528	1.285	0.724	1.091	4370472	3427279
4452	2688568	2855786	2729080	0.418	0.211	0.593	10.77	8.16	250577	1235854	8273434	0.404	0.636	0.469	1333770	1623708
4459	1927416	2097828	1769049	0.466	0.408	0.638	9.37	6.50	196010	901221	5794293	0.498	0.551	0.536	1036478	1005514
4470	1057309	894172	1128722	0.887	0.569	0.344	5.93	5.03	93524	297598	3080203	0.596	0.397	0.587	343330	357695
4511	661689	623399	497505	1.133	1.815	0.910	1.49	1.72	377658	328422	1782594	1.309	0.278	0.784	464894	505396
4557	455048	357863	318264	2.015	0.383	1.014	5.39	5.77	72063	182149	1131175	1.217	0.198	0.708	289813	316472
4558	1965278	1872429	1729763	0.494	1.103	0.974	7.55	9.13	156903	908619	5567470	0.848	0.541	0.726	906406	1068127
4568	838165	593251	719917	0.369	0.436	0.505	9.11	5.81	115190	143728	2151333	0.433	0.316	0.535	591672	500466
4583	354034	389925	371991	0.452	0.392	0.373	9.97	6.99	31871	17459	1115950	0.405	0.196	0.547	183275	169726
4611	1019677	1343382	1204285	0.458	0.744	0.257	1.58	1.31	1040062	496022	3567344	0.498	0.432	0.546	945095	1042158
4635	541180	498965	578417	0.386	0.133	0.652	11.44	7.27	70313	213245	1618563	0.403	0.259	0.536	454179	386006
4665	605496	759192	672292	0.522	0.192	0.065	17.93	10.24	21043	36003	2036980	0.248	0.304	0.480	191014	161604
4692	290922	222811	211741	0.136	0.407	0.041	1.92	1.00	159006	44860	725474	0.191	0.139	0.528	169762	118904
4693	40360	37870	37103	0.062	0.056	0.089	3.42	2.94	23176	107704	115333	0.068	0.033	0.565	47224	52273
4720	1564747	1033927	673607	0.199	0.565	0.477	7.45	4.56	228338	210115	3272281	0.372	0.411	0.496	888728	787040
4740	564546	490967	397903	0.458	0.587	0.319	6.27	4.48	40595	148043	1453416	0.464	0.240	0.554	148533	132648
4741	195268	158205	139993	0.470	1.426	0.341	10.31	10.05	15138	56150	493466	0.740	0.102	0.598	98381	113768
4807	3866	3026	28814	0.062	0.211	3.983	12.91	9.28	113	130	35706	3.239	0.017	0.627	963	786
4808	23523	27786	24628	0.130	0.070	2.292	8.43	9.31	2542	790	75937	0.809	0.025	0.588	13274	17681
4809	109458	101500	92848	0.836	0.106	0.512	7.74	9.28	18796	9977	303806	0.493	0.068	0.576	88317	130821
4811	18440	31338	32477	0.062	2.297	1.089	6.63	9.15	6794	5431	82254	1.319	0.026	0.601	28548	47271
4812	1839	135091	174279	0.023	0.027	0.089	8.43	9.22	537	0	311209	0.062	0.070	0.546	2602	3675
4813	180091	337961	253529	0.195	0.681	2.656	7.74	9.22	25674	161811	771581	1.217	0.147	0.675	141385	179635
4815	1352555	2435726	2274498	0.827	0.550	1.062	8.57	9.06	254391	1054584	6062779	0.804	0.562	0.707	1623511	1769959
4817	8717	16598	12158	1.901	0.000	0.000	3.63	4.34	4408	862	37473	0.442	0.017	0.580	9777	14405
4819	32615	27210	43211	1.931	1.138	2.858	2.13	2.52	9558	50070	103036	2.110	0.030	0.628	13480	18332
4823	700	857	1242	0.077	43.849	0.083	1.75	2.08	913	0	2799	13.480	0.010	0.711	1197	1440
4902	309398	889486	731063	1.159	1.123	0.886	5.46	6.06	41034	241559	1929948	1.039	0.293	0.716	169090	192695
4923	126980	112054	89392	0.534	0.868	1.835	3.16	2.79	32605	130089	328427	1.002	0.073	0.613	66528	69443
5022	10317238	9343889	8578730	0.464	0.694	0.572	9.70	8.87	923710	7395982	28239857	0.573	0.856	0.574	5421145	5525538
5040	2186217	1669575	2953843	0.202	0.983	0.241	27.54	20.25	62695	275695	6809634	0.411	0.590	0.481	874863	789108
5057	3158515	3123971	2449114	0.394	0.610	0.802	19.50	19.43	173618	1452535	8731599	0.586	0.649	0.584	2085124	2172204
5102	1320230	1043734	1047667	0.486	0.593	0.132	9.39	7.21	120846	391810	3411630	0.410	0.421	0.510	609549	586572
5146	547945	681364	627500	0.802	0.782	0.396	9.46	10.21	85745	309271	1856810	0.658	0.286	0.604	516068	587318
5160	678035	568740	572779	0.264	0.261	0.782	5.72	5.93	110967	80293	1819554	0.426	0.282	0.538	360001	428019
5183	16842090	15442128	12637435	0.615	0.426	0.553	5.69	5.08	2610765	8861174	44921653	0.532	0.904	0.537	8409513	8561624
5188	725827	671872	599644	0.424	0.475	0.357	5.68	5.95	123638	284744	1997343	0.421	0.300	0.534	394960	476488

EXHIBIT I (continued)

CLASS	PI1	PI2	PI3	XI1	XI2	XI3	RATE79	RATE82	PAYROLL	ACTLOSS	PI	XI	ZI	UI	ELOSS	NCCIELOS
5190	10881175	10192630	7727757	0.553	0.423	0.397	5.22	3.85	1878430	4142254	28801562	0.465	0.858	0.482	4977017	4724015
5191	1577590	1574190	1449725	1.072	0.359	0.541	1.73	1.64	1130519	2099395	4601504	0.661	0.494	0.621	1279862	1391870
5192	1340288	1418106	1133537	0.639	0.851	0.996	4.38	4.64	268773	626916	3891931	0.820	0.453	0.690	855976	977222
5215	1868594	1424012	960914	0.626	0.417	0.728	10.79	9.91	117689	967602	4253520	0.579	0.475	0.581	777113	788621
5221	8552400	7873243	6233493	0.352	0.484	0.480	9.59	6.60	845125	5531666	22659136	0.433	0.827	0.459	3919012	3863239
5222	1266600	1448136	1511218	0.430	0.296	0.830	15.19	13.39	78829	726873	4225954	0.527	0.473	0.556	701626	697175
5223	297806	324050	289172	0.095	0.075	0.172	14.34	7.06	15346	8126	911028	0.112	0.167	0.503	116755	74636
5348	752918	707044	658042	0.621	0.376	2.547	6.16	7.99	120310	823951	2118004	1.138	0.313	0.756	590283	628989
5403	14427998	14164705	12141251	0.528	0.516	0.814	10.70	9.70	1229627	10847540	40733954	0.609	0.896	0.606	8402935	8238737
5437	1709170	1469425	1229307	0.718	0.461	0.504	6.12	5.81	264916	595404	4407902	0.572	0.484	0.577	986581	1038917
5443	169794	167766	179112	0.040	0.319	1.486	5.20	6.78	42220	45090	516672	0.632	0.106	0.587	135895	186191
5445	2300275	1793603	1445326	0.449	0.700	1.538	5.24	6.83	417280	2586405	5539204	0.814	0.540	0.707	1630189	1853808
5462	1107550	1004201	854136	0.417	0.546	0.486	8.21	7.29	146795	576960	2965887	0.481	0.388	0.543	689372	728075
5479	1500022	1437969	1085784	0.539	0.379	0.651	8.45	6.82	177678	1093476	4023776	0.512	0.461	0.550	869768	862570
5480	822192	985846	860072	0.438	0.381	0.235	10.68	7.13	85847	647937	2668109	0.351	0.363	0.498	481482	407436
5506	4950399	5203370	4849670	1.007	0.581	0.416	9.92	10.46	465543	4035222	15003439	0.668	0.760	0.648	3151809	3406432
5509	5326146	8081051	8021272	0.649	0.508	0.548	9.22	7.54	377439	3072049	21428469	0.558	0.819	0.563	2062943	2069825
5538	11450218	10996745	8919198	0.533	0.556	0.570	7.91	7.04	1517346	8697820	31366160	0.551	0.868	0.556	7026207	7166294
5551	9341150	8775226	6970244	0.383	0.488	0.359	27.72	17.46	357681	4308220	25086619	0.413	0.841	0.440	4594969	4482763
5606	5628626	4983361	3584432	0.416	0.371	0.377	5.28	3.36	1151756	1609170	14196420	0.390	0.750	0.438	2808325	2614429
5610	480126	513642	162137	0.455	0.054	0.898	8.15	6.25	31287	22261	1155905	0.339	0.202	0.533	143268	130729
5645	10470971	8724009	5879962	0.470	0.576	0.314	9.30	6.43	915514	5212561	25074942	0.470	0.841	0.488	4377823	4326434
5651	904120	660285	494851	0.542	0.741	0.246	9.30	6.43	102611	457269	2059255	0.535	0.307	0.568	570802	457797
6003	1132577	814322	675441	0.387	0.293	0.808	24.91	23.04	32833	40060	2622340	0.466	0.359	0.541	465841	487925
6204	1265337	1216055	968484	0.463	0.439	0.461	16.03	12.21	66579	643190	3449875	0.454	0.424	0.528	593760	562030
6217	11149911	10186845	8606849	0.469	0.321	0.288	12.72	7.54	915909	6072388	29943606	0.366	0.863	0.396	4860874	4706854
6229	872136	884324	731464	0.316	0.411	0.376	14.23	8.80	48864	329314	2487924	0.368	0.348	0.508	371950	297555
6233	773141	637802	621389	0.744	0.082	0.483	9.79	9.86	58756	163178	2032332	0.456	0.304	0.544	329680	371183
6306	7378522	4995746	3522883	0.408	0.356	0.566	19.16	13.18	306944	2509986	15897151	0.427	0.770	0.462	2865211	2667500
6319	2048806	1602707	1024810	0.286	0.469	0.519	12.09	7.86	169039	1020021	4676324	0.400	0.498	0.491	1057990	896035
6325	944919	968089	753434	0.549	0.585	1.202	8.81	10.02	138565	1410219	2666443	0.746	0.363	0.642	825656	957323
6400	372763	337771	272674	0.602	1.372	0.554	8.28	10.00	48531	164972	983208	0.853	0.178	0.630	266916	341040
6504	1485381	1984456	1774167	0.611	0.391	0.532	9.67	6.64	154186	725333	5244004	0.501	0.527	0.539	847424	801421
6834	1518155	1243933	1036946	0.915	0.839	1.459	5.09	5.87	214622	1103040	3799033	1.039	0.447	0.786	905080	992243
7219	41660087	42308736	33690828	0.585	0.592	0.608	10.82	10.82	3299246	24118052	117659651	0.594	0.961	0.594	22336456	22332516
7222	194184	402999	352555	0.273	0.770	0.251	20.10	17.18	14973	76756	949738	0.475	0.173	0.564	178777	200549
7230	2636169	2294613	1957225	0.549	0.440	0.577	3.69	2.92	794574	3404102	6888006	0.520	0.593	0.546	1685545	1623026
7360	418345	618610	571829	0.105	0.284	0.843	13.32	9.34	20695	36053	1608784	0.436	0.258	0.544	158152	154612
7380	11802698	12023099	11568520	0.836	0.737	0.711	4.83	5.22	2399602	10632558	35394317	0.762	0.882	0.740	9042432	9197067
7390	2591575	2050511	2008441	1.055	0.657	0.894	4.97	5.54	543336	3110476	6650528	0.884	0.585	0.758	2158368	2140682
7403	1008410	1063868	970189	0.423	0.638	0.409	3.85	2.96	428094	1128083	3042467	0.494	0.394	0.547	950765	894551
7405	11746	10824	5936	0.000	0.010	0.263	4.12	2.65	6602	19180	28506	0.058	0.015	0.574	16457	13159
7421	452951	420395	468875	0.102	2.278	1.658	6.20	7.51	68816	89361	1342221	1.327	0.226	0.750	337369	387599
7423	1274829	1074823	960187	1.166	0.327	0.572	5.60	4.59	181808	212770	3309840	0.721	0.414	0.640	686268	637670
7502	492558	374034	397113	0.540	0.291	0.948	4.38	3.94	105330	64283	1263705	0.594	0.216	0.585	284292	312769
7515	562484	537835	512213	0.097	0.080	0.308	4.66	2.32	74137	70549	1612531	0.158	0.258	0.473	172060	131299
7520	1044117	1168265	1248718	0.445	0.379	0.293	5.75	3.39	153349	733127	3461100	0.368	0.424	0.491	456416	402029
7538	1027057	1130487	1056093	0.420	0.622	0.451	16.86	15.82	44887	176855	3213637	0.501	0.407	0.549	438006	473089
7539	1459157	896546	1469559	0.773	0.355	0.181	4.87	3.56	318485	840458	3825262	0.448	0.449	0.522	852953	804101
7540	558864	568901	514413	0.394	0.388	0.668	7.61	5.84	85099	87548	1642178	0.478	0.262	0.555	378585	378255
7580	558444	601884	767212	0.701	0.247	0.747	5.10	4.19	86733	422196	1927540	0.577	0.293	0.581	270725	272555
7590	218462	190418	210226	1.694	0.414	0.926	8.91	7.37	27280	40845	619106	1.040	0.123	0.638	163481	158189
7600	1098243	1230926	1092591	0.868	0.493	0.465	2.70	2.28	408908	965146	3421760	0.604	0.422	0.591	688154	715254
7601	153075	173370	193791	4.912	0.706	6.877	21.55	26.11	9123	344277	520236	4.242	0.106	0.971	201178	166936
7610	929693	839075	711205	0.381	0.201	0.257	1.06	0.55	987596	914241	2479973	0.285	0.347	0.479	528472	427807
7704	4246260	4355054	4552100	0.632	0.535	0.423	7.98	5.97	407828	1978162	13153414	0.527	0.735	0.542	1858452	1791102

EXHIBIT I (continued)

CLASS	PI1	PI2	PI3	XI1	XI2	XI3	RATE79	RATE82	PAYROLL	ACTLOSS	PI	XI	ZI	UI	ELOSS	NCCIELOS
7720	8960542	10707376	10416162	0.759	0.640	0.562	5.27	4.85	1409822	6489913	30084080	0.649	0.864	0.640	5007390	5068850
7855	633968	626859	563345	0.391	0.347	0.185	26.27	15.85	21557	194835	1824173	0.312	0.282	0.506	301958	230221
8001	563211	503560	418058	0.301	0.250	1.260	2.59	1.69	242768	356233	1484829	0.553	0.243	0.575	381107	326477
8006	2306843	2035575	1575736	0.789	1.164	0.794	3.96	4.40	710474	1905943	5918154	0.920	0.556	0.770	2282538	2559021
8008	4827819	4825172	4500191	0.499	0.368	0.501	1.96	1.12	2448504	2681423	14153182	0.455	0.749	0.487	2461890	2370990
8010	4235800	3917308	3291833	0.516	0.565	0.560	2.62	1.91	1671705	3211085	11444941	0.546	0.707	0.556	2567879	2522521
8013	376639	331175	288103	1.151	0.621	0.739	0.81	0.80	493402	488083	995917	0.856	0.180	0.631	265858	314098
8017	8655017	7715904	6904165	0.813	0.554	0.603	2.26	1.81	4189113	6642611	23275086	0.665	0.831	0.651	6493368	6446930
8021	2066563	2290522	2378461	0.606	0.355	0.442	12.44	7.68	152737	765940	6735546	0.463	0.588	0.512	1024841	933423
8031	894430	863635	801416	0.423	1.393	0.475	5.84	5.19	166275	542852	2559480	0.767	0.354	0.647	662533	671427
8032	99148	110074	95410	1.306	2.108	0.787	1.98	2.23	62086	51907	304632	1.433	0.069	0.640	82967	111908
8033	10703932	9424974	7464023	0.970	0.591	0.877	4.12	4.32	2408123	4703833	27592929	0.815	0.853	0.781	8165487	8135199
8039	2521491	2980779	2896836	0.524	0.579	0.695	3.34	2.44	784983	1634935	8399106	0.603	0.640	0.595	1644567	1678634
8044	4103566	4231479	3428600	0.699	0.363	0.558	4.04	2.92	886878	3102440	11763644	0.537	0.713	0.550	2077145	2060731
8046	504131	446326	347115	0.357	0.201	0.458	3.19	1.90	170160	113045	1297572	0.330	0.220	0.527	301274	249027
8047	167798	188298	209453	0.212	0.174	0.095	4.38	2.55	33913	303747	565549	0.156	0.114	0.534	83533	68673
8050	499006	555130	506930	0.703	0.282	0.688	2.44	1.84	239716	138510	1561066	0.548	0.252	0.574	353538	362223
8058	784830	562159	420086	0.319	0.188	0.264	3.22	1.77	276992	299651	1767075	0.264	0.276	0.494	464728	392980
8102	96541	85570	73121	0.286	0.726	0.251	4.24	4.85	17474	8711	255232	0.423	0.059	0.573	44716	67299
8103	213741	332213	310834	0.354	0.603	0.662	11.54	7.97	6366	190061	856788	0.562	0.159	0.579	44824	40290
8106	11793278	11070371	10659259	0.457	0.542	0.412	19.10	12.62	490877	3737411	33522908	0.471	0.876	0.485	4787921	4628024
8107	3115221	2790487	2294525	0.401	0.647	0.709	6.56	5.44	465402	1222285	8200233	0.571	0.634	0.575	1850291	1843118
8111	936887	812610	767748	0.832	0.940	0.270	4.71	4.40	200507	677751	2517245	0.696	0.350	0.622	618861	667518
8116	1721662	1491526	1394697	0.586	0.598	0.351	6.11	4.35	298254	362050	4607885	0.519	0.495	0.551	1057743	1018710
8209	308896	266365	247365	1.036	0.249	1.362	8.96	7.79	47376	229746	822626	0.879	0.154	0.628	280924	295206
8215	204716	135213	109178	0.169	1.253	0.074	7.59	6.04	31597	538345	449107	0.472	0.094	0.572	144510	152020
8227	2564144	2147056	1632457	0.726	0.560	0.446	5.18	5.13	524388	900885	6343657	0.598	0.573	0.591	1691966	1776828
8233	25376	29450	21014	0.000	3.432	0.189	21.52	11.82	1234	211	75839	1.385	0.025	0.602	16855	11228
8235	418743	486868	430558	0.128	0.144	0.264	7.93	4.66	72075	257215	1336169	0.178	0.225	0.491	295825	264531
8263	95260	99711	160720	0.024	0.096	3.206	22.20	18.10	4106	31593	355692	1.482	0.078	0.652	62647	58600
8264	390122	331980	279266	0.933	1.072	0.590	23.01	19.19	17156	280027	1001368	0.883	0.180	0.636	264760	263607
8265	4770013	3911813	4270895	0.807	0.530	0.541	22.54	18.79	166582	1386262	12952721	0.635	0.732	0.621	2457687	2493318
8279	429795	346655	348981	0.278	0.471	0.347	10.28	7.32	33365	147449	1125432	0.359	0.198	0.538	194493	195357
8288	116271	85949	76630	0.080	0.181	4.532	5.49	6.24	16790	109564	278850	1.334	0.064	0.630	61209	83716
8291	161817	206003	197906	0.048	0.188	0.456	8.90	6.36	25995	170124	565727	0.242	0.114	0.543	132486	128375
8292	2898214	3040668	2571443	0.827	0.396	0.517	11.08	8.69	261585	1115014	8510325	0.579	0.643	0.580	1772327	1752679
8293	3203262	3199470	2750337	0.322	0.604	0.513	18.71	12.65	124897	1389675	9153069	0.478	0.659	0.514	1264627	1190742
8304	1538645	1543099	1514094	0.816	0.288	0.736	7.23	6.04	231210	786002	4595838	0.612	0.494	0.597	1051826	1081079
8350	3408926	3508183	3050023	0.509	0.581	0.639	7.69	6.37	414059	1599941	9967133	0.574	0.678	0.577	1934562	1945887
8385	1112465	1274049	1009490	0.695	1.016	0.306	10.35	9.20	114764	634085	3396004	0.700	0.420	0.632	790607	814072
8387	13382393	13958051	13017857	0.704	0.436	0.492	7.17	5.07	1708457	6933269	40358302	0.543	0.895	0.547	7063586	7030796
8392	375357	408405	484371	0.562	0.887	0.199	4.91	3.54	101123	306668	1268133	0.528	0.216	0.570	298438	284856
8393	4018520	3661562	2988391	0.580	0.464	0.469	6.23	4.48	562093	1914058	10668473	0.509	0.693	0.531	1960802	1899708
8500	1007959	877722	795934	0.382	0.741	0.849	19.28	17.22	44419	622893	2681615	0.638	0.364	0.603	543758	604906
8606	68108	777156	529766	0.034	0.634	0.246	14.43	9.07	8250	17363	1375030	0.455	0.230	0.553	69360	59058
8719	33601	41684	21714	0.003	5.144	0.007	3.43	2.80	9704	24884	96999	2.213	0.029	0.629	22079	21400
8720	405725	416034	388562	1.067	1.338	1.025	2.15	2.50	196499	84974	1210321	1.147	0.209	0.700	311665	384155
8742	15027070	14610494	12461295	0.664	0.463	0.551	0.85	0.69	17968009	9088589	42098860	0.561	0.899	0.563	9057893	9068473
8745	532432	331748	551806	0.163	0.419	0.349	7.11	3.91	39185	188785	1415986	0.295	0.235	0.515	151134	121918
8748	2195084	2176224	1800633	0.308	0.148	0.754	1.16	0.70	1525051	1170389	6171941	0.382	0.567	0.469	873588	783830
8800	180266	134787	123832	2.606	1.354	2.055	1.36	1.54	119315	172829	438885	2.066	0.092	0.719	122983	143688
8803	155186	142079	119842	0.503	1.113	0.916	0.17	0.20	1087727	314708	417106	0.830	0.089	0.604	117711	167902
8810	19674841	18494077	16281312	0.725	0.545	0.497	0.38	0.30	53363602	13813843	54450230	0.596	0.920	0.595	12709373	12699759
8829	16141273	15802318	14923641	0.753	0.651	0.716	7.40	5.86	2076701	12688059	46867232	0.707	0.908	0.696	11263976	11661565
8831	490844	445809	350497	0.277	0.806	0.850	2.36	1.83	223961	90361	1287150	0.616	0.219	0.590	328413	323128
8832	3216701	2658083	2092592	0.480	0.414	0.764	0.61	0.43	6248490	1092473	7967376	0.533	0.628	0.551	2213998	2088378

EXHIBIT I (continued)

CLASS	PI1	PI2	PI3	XI1	XI2	XI3	RATE79	RATE82	PAYROLL	ACTLOSS	PI	XI	ZI	UI	ELOSS	NCCIELOS
8833	4519987	7496166	7622172	0.580	0.528	0.748	1.62	1.33	2687172	2422170	19638325	0.625	0.805	0.617	2830469	2922525
8835	1542399	1656754	1496793	1.207	0.763	0.629	3.20	3.28	476618	1205124	4695946	0.866	0.499	0.724	1163587	1317573
8837	726135	929839	841591	0.494	0.930	0.510	5.43	4.31	124289	662406	2497566	0.662	0.348	0.610	433769	468411
8868	5881087	8037455	8405740	0.595	0.661	0.545	0.44	0.37	11920613	2492001	22324282	0.600	0.825	0.597	3298311	3417841
8901	182220	107554	104326	0.052	0.067	0.066	0.46	0.50	535544	456448	394100	0.060	0.085	0.538	139668	208128
9014	3713463	3724307	3138390	0.750	0.769	0.658	6.20	5.67	655949	3842141	10576160	0.730	0.691	0.684	2931264	3165815
9033	64844	41776	38445	0.225	0.255	2.647	3.75	3.62	16566	154485	145064	0.876	0.038	0.593	38849	46847
9040	2455879	4217572	4440302	0.581	0.872	1.045	5.32	5.55	396519	1987999	11113752	0.877	0.701	0.789	1753263	1917773
9052	4660359	4742673	4784389	0.587	0.634	0.774	6.19	4.77	698409	2557158	14187421	0.666	0.750	0.645	2936892	3066357
9058	1938505	1688192	1060873	0.768	0.797	0.959	4.02	3.76	462289	1704957	4687570	0.822	0.499	0.702	1373950	1471427
9060	2360563	2187406	1930050	0.607	0.395	0.675	3.99	2.84	664463	1387950	6478019	0.556	0.578	0.567	1583380	1563056
9061	1642685	1646871	1285497	0.658	0.536	0.593	3.48	2.60	538152	1228969	4575052	0.596	0.493	0.589	1162256	1150280
9063	482492	447299	451499	0.447	0.494	0.569	2.01	1.51	285828	293017	1381290	0.502	0.231	0.564	341237	354440
9079	30502044	30189414	25907410	0.509	0.479	0.514	4.02	2.21	7529275	22208301	86598869	0.500	0.948	0.504	16087046	15463790
9101	8527562	11719227	12239911	0.668	0.807	0.806	5.55	5.41	1363581	4334653	32486700	0.770	0.872	0.746	5950705	6190271
9102	1066629	1185761	1067543	0.770	0.340	0.294	4.53	2.99	163540	402062	3319933	0.463	0.414	0.533	416041	393584
9103	46305	74714	65678	0.292	0.813	0.467	5.55	4.26	5165	6552	186697	0.562	0.046	0.581	17559	17349
9154	710404	636055	568681	1.037	0.507	0.152	2.87	2.07	264885	267078	1915141	0.598	0.292	0.587	470137	435417
9156	78026	56303	48321	0.169	0.022	1.699	0.95	1.03	84759	23519	182650	0.528	0.046	0.580	49189	67583
9170	474549	538312	540464	1.255	0.420	0.262	40.22	34.27	9701	723697	1553324	0.620	0.252	0.592	243253	264815
9178	156237	122975	183758	0.153	0.220	0.132	8.16	5.48	12558	37990	462970	0.163	0.097	0.542	58493	53168
9179	686853	650957	665038	0.552	0.458	0.425	20.13	15.10	34808	227424	2002849	0.479	0.301	0.551	407014	394580
9180	477633	526911	406398	0.132	0.792	0.700	12.92	8.93	29940	534738	1410942	0.542	0.234	0.573	233475	213858
9182	60211	73786	66843	1.302	0.026	0.754	3.54	2.57	5912	955	200840	0.651	0.049	0.586	12913	11978
9186	234050	303365	267169	0.481	0.291	0.298	36.78	22.10	5385	47046	804583	0.349	0.152	0.547	114126	92044
9220	715318	736163	703966	0.733	0.545	0.489	6.53	5.46	110169	484504	2155447	0.589	0.316	0.584	443048	478658
9402	603852	553395	460424	1.041	0.409	0.469	6.23	5.37	80923	931210	1617670	0.662	0.259	0.603	320255	338446
9403	5951168	5701963	5470534	0.593	0.768	0.413	17.59	14.32	300128	3556465	17123666	0.594	0.783	0.591	3288505	3337157
9410	4074116	4801123	4587642	0.652	0.490	0.524	7.35	5.38	319975	2145720	13462881	0.551	0.740	0.559	1385258	1360005
9519	1780055	1807575	1592850	0.682	0.246	0.333	5.10	3.05	348285	969505	5180480	0.423	0.524	0.499	933486	806911
9521	1378453	1253369	1092400	0.528	0.713	1.222	4.78	5.76	269271	1002330	3724223	0.794	0.442	0.676	916473	1121684
9522	988738	967683	833211	0.481	0.643	0.396	4.22	3.13	183846	542245	2789633	0.512	0.373	0.556	454461	443236
9545	55891	51234	46135	0.173	0.034	1.308	5.20	6.50	18172	31938	153260	0.468	0.040	0.578	57516	80152
9549	399810	383087	411577	0.700	0.161	0.290	16.19	12.99	27024	166386	1194473	0.386	0.207	0.542	249704	240112
9558	337279	327073	329166	0.240	0.945	1.430	11.19	12.28	31828	207857	993519	0.866	0.179	0.633	237587	258826
9559	163032	134650	125235	0.203	0.102	0.361	5.80	4.59	26567	56806	422918	0.218	0.090	0.550	89228	91905
9586	678594	581205	516081	0.383	0.427	0.642	1.04	0.71	688485	304793	1775880	0.473	0.277	0.552	416461	393868
9600	1643	2750	1592	0.000	1.738	0.000	1.70	2.01	1108	143	5985	0.799	0.011	0.584	1161	1687
9620	573137	493516	451331	0.254	0.393	0.298	2.34	1.63	256258	606673	1517983	0.312	0.247	0.515	325704	330334