DEVELOPMENT OF A PREDICTIVE MODEL TO ASCERTAIN PROBABLE SAFETY RATINGS FOR MOTOR CARRIER FIRMS: A NATION-WIDE PERSPECTIVE

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ABSTRACT

In every industry, safety is a top priority. This is particularly true in the trucking industry, as evidenced by the increases in roadside inspections and safety reviews conducted each year and new legislation implemented. However, some costs to the industry, and ultimately society, from these requirements may be able to be diminished. Safety reviews, in particular, can be very time consuming. Previous research has shown, however, that many other data items that the Federal Highway Administration collects are highly correlated with the outcome of these reviews. Therefore, this project examines the feasibility of developing a model from this other data to ascertain the likelihood of a certain safety rating. This would enable efforts to be concentrated on the motor carrier firms with the least probability of achieving a Satisfactory rating and reduce the need to visit every firm. A preliminary analysis is conducted using only information from North Dakota to get a feel for the data; then a comprehensive analysis is performed utilizing all motor carriers in the data base. In addition, reviews of other related research are given.

LIST OF ACRONYMS

DOT	Department of Transportation
FMCSR	Federal Motor Carrier Safety Regulations
MCMIS	Motor Carrier Management Information System
MCSAP	Motor Carrier Safety Assistance Program
NHTSA	National Highway Traffic Safety Administration
OMC	Office of Motor Carriers
OOS	Out-of-Service
SR/CR	Safety Review/Compliance Review
VMT	Vehicle Miles Traveled

INTRODUCTION AND LITERATURE REVIEW

Safety is a very important issue with regard to the social and economic well-being of a country. Although the number of fatal traffic accidents per year has been steadily decreasing,[1] there is always a desire to improve safety as much as possible. The ability to develop safety ratings for motor carrier companies is an important input for improving safety as well as for transportation planning and policy development. However, the cost of obtaining data from personal visits to motor carrier companies may be able to be avoided if one is able to ascertain probable safety ratings accurately with other available data. Therefore, a model that could predict safety ratings from available motor carrier data already collected and maintained by the Federal Highway Administration could prove to be a very cost-effective analysis tool.

The main purpose of the current research project is to examine if information obtained from the roadside inspections of a carrier can be utilized in conjunction with other knowledge about that carrier, such as its size or classification, to aid in targeting carriers for review and/or ascertaining probable safety ratings for them. These reviews and safety ratings are important for judging the safety fitness of a carrier and helping to identify firms with safety problems. Each state is allocated funds through the Motor Carrier Safety Assistance Program (MCSAP) to conduct these reviews and inspections. The aforementioned data are maintained in the Motor Carrier Management Information System (MCMIS) by the Office of Motor Carriers (OMC). Included in MCMIS is information concerning commercial motor carriers that are subject to the Federal Motor Carrier Safety Regulations (FMCSR).

A brief review of studies which have utilized the above mentioned data is given for clarification of the current project's development. One of the initial studies of inspections and

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[1] U.S. Department of Transportation, *Motor Carrier Activities of the Federal Highway Administration*, September 1993

accidents was conducted by McDole (1977) and was initiated by OMC (then called the Bureau of Motor Carrier Safety) to "determine the effect of proper commercial vehicle inspection and maintenance procedures on safety, and to document the need for improved or modified inspection and maintenance requirements in the FMCSR, Section 396."

The main conclusion of this study was that there is a strong relationship between quality maintenance and inspection procedures and a decline in accidents related to defects. The point was made that larger firms appear to have better maintenance and inspection procedures than smaller or private firms, as it is more economically beneficial for them to do so. Further results indicated that the defects most likely to cause accidents are those associated with the brakes, tires/wheels, and lights. Since these defects are all detectable visually, the author believed that daily driver inspection is the most effective way to discover these defects. In addition, frequent periodic inspections and repairs by maintenance personnel of the carrier were suggested. Roadside inspections were then seen as a backup to the above to provide incentive to maintain vehicles (to avoid sanctions) and also to cause repair of vehicles found with defects.

A second study, conducted by Michael Patten, Joseph Carroll, and Evelyn Thomchick (1989), had the main objective of comparing roadside inspections with the causes of accidents involving large trucks. The study began by addressing the issue that accidents are unique occurrences that involve many interrelated factors - driver, vehicle, and environment - and that there are no quick and simple explanations as to why trucks are involved in accidents.

A brief description of the inspection process was given which emphasized that items which are crucial to operating the vehicle safely are checked. Violations found were divided into two categories: those such as record keeping or minor vehicle defects not posing any immediate danger, and more severe items that require a driver/vehicle to be placed out-of-service (OOS) until the violation is fixed.

Some findings of this study were that in all of the data sets examined, the vast majority of OOS violations found were vehicle related, the most common involving the brake system. Driver-related OOS violations were much less common. It was noted that this is due to the design of the inspection (i.e., there are only a few items a driver can be placed OOS for, while there are many that can cause a vehicle to be). Also, it is difficult to tell how accurate drivers' logbooks actually are, or how fatigued they may be due to their actions before going on duty. Further, the study found that the driver was the prime cause of the huge majority of truck accidents. In conclusion, the authors stated that although roadside inspections "provide a useful tool for enforcement officials to remove some potentially unsafe vehicles from the highway," they do not concentrate enough on factors related to drivers that cause accidents.

A third major study of roadside inspection data was conducted for OMC by Jack Faucett Associates (JFA) (1991). It had several objectives, including: (1) to determine if OOS criteria influenced a decline in accidents; (2) to determine what the relationship is between carriers' roadside inspection performance, their accident rate, and their safety/compliance review record; and (3) to examine the relative efficiency of the OOS criteria.

The 1984-88 MCS 50-T files were used to establish the frequency of certain mechanical defects in accidents reported by individuals. These files consist of forms carriers were required to submit when there had been a reportable accident (one where there was a death of a person, bodily injury to a person requiring immediate medical treatment away from the accident site, or total property damage of $4,400 or more). Carriers are no longer required to submit these forms and accident data is now collected and uploaded from the states, and these accidents are now referred to as recordable instead of reportable. Additionally, property damage is no longer a factor, but whether or not a vehicle was towed from the scene of the accident is. Although there are weaknesses associated with these files (i.e., under-reporting of accidents or not reporting mechanical defects present), the authors believed that this would not affect their analysis. The reason given was that they were simply determining the probability of a specific defect, present at the time of the accident, causing the accident. Defects suitable for their analysis were found in 3.45% (5,702) of the records in the data base. In addition, the authors used several studies to determine the average expenses associated with injuries and deaths.

A second data source was the 1988-89 SAFETYNET data. This source contains inspection records for motor carriers. After eliminating inspections of carriers without a Department of Transportation (DOT) census number and those of buses, 812,978 records were available for analysis. Violations in the data set were labeled as either OOS or non-OOS; classified as driver, vehicle, or hazardous materials; and given a severity rating from one (least severe) to seven (most severe). To develop carrier profiles, only those carriers with three or more inspections in the year prior to their most recent safety/compliance review (SR/CR) were used, for a total of 5,830 carriers.

A third data source employed was the 1988-89 SR/CR file. After records with multiple carrier reviews were eliminated, 41,253 carriers were available to analyze. As aforementioned, 5,830 of these were matched by having three or more inspections in the year prior to their review. Actual analysis, however, used only 5,805 carriers, as 25 had no annual vehicle miles traveled (VMT) data available.

A final data source utilized was the state accident data base managed by the National Highway Traffic Safety Administration (NHTSA) which contains accident reports filed by investigators or state police for all types of vehicles and, thus, is seen to be more reliable than the MCS 50-T files. These data were used for the first objective of whether the OOS criteria have influenced a decline in accidents. Since the authors were examining differences in accident rates between the year the state entered the Motor Carrier Safety Assistance Program (MCSAP) and two years later, and because they also required a breakdown of vehicle types and a precise identification of vehicle defects, only thirteen states were available for this analysis.

Of the thirteen states examined, significant decreases were reported in the defect accident rate in nearly every one between the year the state entered the MCSAP program and two years later. The mean rate of decrease was .032 accidents per million miles (from 0.203 to 0.171) which was significant at the 0.01 level. This occurred while the number of roadside inspections conducted increased almost three times. Non-truck accidents for the same states and years remained nearly constant, while truck defect accidents decreased by over 12% (overall truck accidents decreased by 2%). Examining individual defects, the authors reported that brake defect accidents declined the most (15%), followed by tire, steering, and other (10-12%), and then lights (5%). The authors concluded by stating that their "analyses indicate that the application and enforcement of the OOS criteria through the MCSAP roadside inspection program have had a significant impact in decreasing the rate of truck accidents where mechanical or safety defects were cited as primary contributing factors."

Under the second objective, comparisons were made between the average OOS performance for carriers rated Satisfactory, Conditional, or Unsatisfactory for each of five groups classified by VMT (vehicle miles traveled). Carriers were classified this way since significant differences were noted between these five groups in inspection performance (i.e., higher VMT carriers had better performance). For carriers in the lowest and highest VMT groups, there were some problems in arriving at conclusions due to the small number of carriers in the fifth group and under-reporting of VMT observed in the first group. For the remaining groups, carriers with an Unsatisfactory rating had a significantly higher percentage of OOS vehicles (and a higher mean number of OOS violations per inspection) than those with a Satisfactory rating. Similarly, those carriers in the second and third groups rated Unsatisfactory or Conditional on Part 396 (Inspection, Repair, and Maintenance) of the SR/CR had significantly worse inspection performance than those rated Satisfactory. There was also evidence of a significant relationship between better inspection performance and "yes" answers to specific questions of the SR/CR (those referring to whether the carrier complies with inspection procedure, whether the carrier can produce maintenance files on a specific vehicle, whether the carrier has a driver safety/orientation program, and whether the carrier reviews its safety compliance status periodically). The authors reached the conclusion that although there were significant relationships between vehicle inspections and SR/CRs, they were not perfectly correlated.

When comparing the OOS measures to accident rates, the authors pointed out that the relationship may differ for small and large carriers. For smaller carriers, if they have a higher OOS rate, they may have a lower accident rate because of their vehicles being placed OOS and repaired. Conversely, for larger carriers, a higher OOS rate may indicate poor overall safety practices, and thus one might expect them to have a higher accident rate.

The authors found that as the size of the carrier increases, the average accident and fatality rates decrease. They also found a positive significant relationship between accident and OOS rates for carriers in the third and fourth groups. It was noted, however, that this analysis did not consider other factors, such as driver error, that may cause accidents. The association seemed to be best with injury and fatality rates and not quite as strong with accident and preventable accident rates (which include fewer serious accidents).

Under the final objective, the goal was to ascertain which violations were the most critical to detect in order to minimize the expense of truck accidents. It was found that accidents with a driveline or fuel system defect were approximately three times more deadly, but brake and wheels/tires defects had the highest costs connected with them as they occurred most often. If one wishes to minimize accidents or accident costs, the authors found that wheels, tires, and the suspension system should receive more inspection time than they did in 1988 and that less attention should be paid to lights, windshield/wipers, and the frame/body.

A follow-up to the above study was conducted recently by the present author (Lantz, 1993) utilizing a sample of 1,334 larger carriers (at least twenty drivers) that had ten or more roadside inspections completed on their trucks in 1990 and 1991 and had received a safety rating between June 1991 and June 1992. Comparing out-of-service rates and violation rates across safety ratings (Satisfactory, Conditional, or Unsatisfactory), a significant (at the 0.01 level) increasing trend was observed overall and also on specific parts of the safety review (i.e., in general these carriers rated Unsatisfactory had higher rates than those rated Conditional, which in turn had higher rates than those rated Satisfactory). These differences were found to be significant utilizing the usual ANOVA F-test with a square root transformation on the dependent variable to stabilize variances.

In addition, it was found that reportable accident rates were significantly positively correlated (again, at the 0.01 level) with out-of-service and violation rates (i.e., a carrier with a higher out-of-service or violation rate will also have a higher reportable accident rate, in general). These results were helpful in confirming that trends in earlier research were still present and in developing the current project.

Work has also been recently conducted linking accident rates to factors other than roadside inspection results. One major study, conducted by Moses and Savage (1992), compared findings of the SR/CRs to accident rates. Utilizing the SR/CR data base for the period of 1986-91, the authors found that accident rates per million miles were lower for larger firms, and that short-trip or private carriers had lower accident rates than long-distance or for-hire carriers. In addition, general freight and specialized carriers were reported to have similar rates, but agricultural carriers' rates were lower, and hazardous materials carriers' rates were higher than others. Finally, it was found that older firms tend to have lower accident rates than newly incorporated firms.

Another area investigated by Bruning (1989) was the relationship between accident rates and profitability in trucking firms. As sources of data, the author used the MCS 50-T accident forms as well as data from the ATA's (American Trucking Associations) *Financial and Operating Statistics* report for 1984. The findings included evidence that as carrier profitability declined, accident rates increased. Other conclusions included that general freight and specialized carriers differed with respect to some accident rate factors. For example, size of the carrier did not influence accident rates for general freight carriers, but did for specialized carriers. Also, it was found that the less time overall that drivers had been employed by the company, the higher its accident rate, but there appeared to be no relationship between accident rates and the percentage of owner-operators employed. Furthermore, the author reports that the state of equipment a company used (i.e., its age or defect rate) accounted for some accident rates, but that weather conditions did not appear to have a significant impact.

A final interesting study reviewed was again conducted by JFA (1993) and relayed an informative discussion of data quality issues. One finding of particular interest was the discovery that some fields with data missing were inputted as zeros instead of as missing values. One specific field where this occurred was the number of reportable accidents. This presents a serious problem if one is using this variable in analysis. JFA's study also found fields where keying errors occurred (as normally expected), with the primary field where this happened being the annual vehicle miles traveled (this number can range from thousands to billions, depending on the size of the firm). They suggested checking the reasonableness of this number by dividing it by the number of power units or drivers the firm reports (this procedure was completed for the data used in the current project). Still, with the volume of data that is collected, inputted, and uploaded from every region of the country, the quality of the majority of it is surprisingly reliable.

PRESENT STUDY

After examining the previous research, one has to ask what is the primary goal? The typical answer is to increase safety by identifying firms that are more likely to be "unsafe." The problem is that safety is usually defined by accident rates, but accidents, as has been shown, are caused by many factors not necessarily related to the company. In addition, the data on accident rates have been shown to be not very reliable. However, a better way to identify "unsafe" firms may be to look at their out-of-service rates. Drivers are required before every trip to examine their truck and equipment to make sure everything is in good working order. Companies should enforce this policy. Therefore, when a truck or driver is placed out-of-service, it is a reflection on the company; and the higher out-of-service rates that a company has, the more "unsafe" that company is likely to be.

Since previous research has shown that these out-of-service rates are associated with the safety rating of the company, it is logical to use them in trying to predict a probable safety rating for a company. As aforementioned, these safety ratings are given after extensive review of the company's records and procedures concerning all the federal regulations, which is very time-consuming. If these ratings could be assigned accurately without having to conduct these reviews, it would prove to be a very useful and cost-effective analysis tool. Thus, this is the motivation behind the current project.

In addition to out-of-service rates, previous research has identified many variables that would be potentially useful in determining safety ratings (e.g., cargo carried, profitability of the firm, year of incorporation, etc.). However, a problem arises in justifying utilization of some of these variables. For example, even though it has been shown that less profitable firms have higher accident rates, it would be hard to justify assigning them an Unsatisfactory rating just because of their profit margin. So, after consulting with the OMC, the variables deemed suitable for analysis were the out-of-service rates, the firm size (as measured by annual total miles), and their classification (these are described in detail below).

Data Used in Analysis

The majority of data used in the present analysis was collected during what is termed a safety review. This is a procedure by which a trained specialist from the Federal Highway Administration visits and examines the carrier to determine if they are in compliance with all relevant federal regulations. Based on the results from this review, the carrier is given a Satisfactory, Conditional, or Unsatisfactory safety rating. This will become the dependent variable in the analysis. Other variables from this procedure include the number of annual miles the carrier travels and their classification.

Additional variables used in analysis were obtained from a roadside inspection. In this procedure, trucks are randomly stopped and inspected as they are traveling. If any serious violations are found, the truck or driver is placed out-of-service until the violation is corrected. Thus, the variables used from this procedure were the number of trucks and/or drivers a carrier has had placed out-of-service.

The above data are input into a system termed SAFETYNET. These data are then uploaded to the main system (MCMIS) in Washington, D.C., where they were obtained for the present project. Data that included all motor carrier firms with a safety review on or after January 1, 1990, were requested from OMC (the request was processed in August of 1993). Firms with less than three roadside inspections in the two years prior to their review were deleted. This was done as previous research has shown that an out-of-service rate is not statistically stable until at least three inspection observations have been recorded, and this variable is regarded as the most important in the present analysis. After this procedure, 15,398 firms were left to analyze. North Dakota firms were sorted out for a total of 289 firms to analyze in the preliminary analysis. After this, a second comprehensive analysis is performed using all 15,398 firms.

Before fitting the model, it might be useful to see how each of the variables is related to safety ratings. So, in addition to the description of the variables, the next section also describes their relationship to safety ratings.

(1) **Classification:** There are three main classifications that a carrier can fall under. These are Authorized-for-hire, Private, and Exempt-for-hire. For-hire carriers are those that

provide service to the public and charge a fee. Private carriers provide service to a firm that owns or leases the vehicle(s) and do not charge a fee (in general). Exempt operations are those that are not regulated by the Interstate Commerce Commission either because of what they carry or their scope of operation. These carriers usually fall under state regulation rather than federal. A carrier may indicate one, two, or all three classifications. Thus, there are seven possible categories. These are listed in Table 1 along with the percentage of carriers in that category with Satisfactory and Not Satisfactory (Conditional or Unsatisfactory) ratings. The categories are sorted from best (highest Satisfactory percentage) to worst.

The table indicates that the carriers in the Authorized-for-hire and Private category have the highest percentage of Satisfactory ratings while those in the Exempt-for-hire and Private category have the lowest. Thus, the Exempt-for-hire and Private category will be used as the reference group in the analysis (all design variables equal to zero). The design variables for the regression model are listed in Table 2.

Table 1. Classification by Safety Rating Percentage (ND Data)

Classification	Satisfactory Percentage	Not Satisfactory Percentage
Authorized-for-hire and Private (n=6)	83.33	16.67
Authorized-for-hire and Exempt-for-hire (n=70)	68.57	31.43
Authorized-for-hire (n=24)	66.67	33.33
Authorized-for-hire, Exempt-for-hire, and Private (n=29)	58.62	41.38
Exempt-for-hire (n=59)	57.63	42.37
Private (n=67)	41.79	58.21
Exempt-for-hire and Private (n=34)	35.29	64.71

Table 2 can be interpreted in the following way. If a carrier indicates it is Authorized-for-hire, then the variable CLA is one (1), and the remaining classification variables are zero (0). Similarly, if the carrier indicates it is Exempt-for-hire, then the variable CLE is one (1), and the remaining classification variables are zero (0). The variable CLP is one (1) if the carrier is Private; CLAE is one (1) if the carrier is Authorized-for-hire and Exempt-for-hire; CLAP is one (1) if the carrier is Authorized-for-hire and Private; and, finally, CLAEP is one (1) if the carrier is Authorized-for-hire, Exempt-for-hire, and Private. Again, the other classification variables would be set to zero (0). If the carrier is Exempt-for-hire and Private (the reference group), all of the above variables are zero (0).

Table 2. Design Variables for Classification

Classification	**CLA**	**CLE**	**CLP**	**CLAE**	**CLAP**	**CLAEP**
Authorized-for-hire	1	0	0	0	0	0
Exempt-for-hire	0	1	0	0	0	0
Private	0	0	1	0	0	0
Authorized-for-hire and Exempt-for-hire	0	0	0	1	0	0
Authorized-for-hire and Private	0	0	0	0	1	0
Authorized-for-hire, Exempt-for-hire, and Private	0	0	0	0	0	1
Exempt-for-hire and Private	0	0	0	0	0	0

(2) **Annual Miles:** The annual mileage of a company is the approximate total miles the company has driven, considering all of its power units and drivers in the 365 days prior to the safety review. Table 3 shows an arbitrary breakdown of this variable and the corresponding safety ratings. Previous aforementioned research has found that larger companies tend to have lower accident rates and also better maintenance and safety procedures, and since these are

considered in determining safety ratings, one would expect that larger companies would also be more likely to have Satisfactory ratings. As the table indicates, this appears to hold true. As the number of annual miles increases, there are a higher percentage of companies with Satisfactory ratings.

Table 3. Annual Miles by Safety Rating Percentage (ND Data)

Annual Miles	Satisfactory Percentage	Not Satisfactory Percentage
0 < miles ≤ 50,000 (n=37)	32.43	67.57
50,000 < miles ≤ 200,000 (n=179)	56.42	43.58
Greater than 200,000 miles (n=73)	64.38	35.62

(3) **Driver Out-of-Service Rate:** This variable is simply the number of drivers the company has had placed out-of-service (as described earlier) in the previous two years prior to its review, divided by the total number of roadside inspections it has had in those two years (it must have had at least three inspections). Table 4 illustrates an arbitrary breakdown of these rates and compares safety ratings. The first two categories are about equal, and then there is a definite decreasing trend in the percent of Satisfactory ratings as the driver out-of-service rate increases. The variable used in analysis is DRVOOSRT.

Table 4. Driver Out-of-Service Rate by Safety Rating Percentage (ND Data)

Driver Out-of-Service Rate	Satisfactory Percentage	Not Satisfactory Percentage
0.0 driver out-of-service rate (n=191)	58.64	41.36
0.0 < driver out-of-service rate ≤ 0.1 (n=33)	60.61	39.39
0.1 < driver out-of-service rate ≤ 0.2 (n=39)	46.15	53.85
Greater than 0.2 driver out-of-service rate (n=26)	38.46	61.54

(4) **Vehicle Out-of-Service Rate:** This is very similar to the driver out-of-service rate, except the total number of vehicles placed out-of-service in the two years prior to the review is divided by the number of roadside inspections in those two years (again, the company must have had at least three inspections). Table 5 demonstrates that the same trend is apparent as that for driver out-of-service rates. The percent of Satisfactory ratings decreases as the out-of-service rate increases. The variable used in analysis is VEHOOSRT.

Table 5. Vehicle Out-of-Service Rate by Safety Rating Percentage (ND Data)

Vehicle Out-of-Service Rate	Satisfactory Percentage	Not Satisfactory Percentage
0.0 vehicle out-of-service rate (n=82)	64.63	35.37
0.0 < vehicle out-of-service rate ≤ 0.2 (n=55)	56.36	43.64
0.2 < vehicle out-of-service rate ≤ 0.4 (n=93)	55.91	44.09
Greater than 0.4 vehicle out-of-service rate (n=59)	40.68	59.32

Procedure Used for Model Development

According to Hosmer and Lemeshow (1989), a procedure to utilize when one wishes to predict a dependent or response variable which is not continuous is logistic regression. In the present case, the response variable is the safety rating of the company that can fall into three categories: Satisfactory, Conditional, or Unsatisfactory. However, the primary interest is in whether a company should receive a Satisfactory rating or not, as those that receive Conditional or Unsatisfactory ratings are required to bring their ratings up to par within a specified period of time. Thus, the greatest of interest is in correctly ascertaining probable Satisfactory ratings and identifying those companies that are more or less likely to receive such a rating. However, the comprehensive analysis does explore predicting both Satisfactory and Unsatisfactory ratings.

Logistic regression is a relatively new procedure that has been mostly utilized in the last 10-15 years with the advancements in computers and available software. It is seen often in the biological fields where scientists wish to study dose-response relationships (i.e., locating at which dose of a chemical a certain percentage of the experimental units will have the desired response). Due to this increase in use, there has been a considerable amount of research conducted on the procedures of logistic regression, and it is generally accepted as a stable and reliable method to use when one has a binary response variable (i.e., Satisfactory rating or not) (Hosmer and Lemeshow, 1989).

The exact general form of the logistic regression model (Hosmer and Lemeshow, 1989) is as follows:

$$\pi \quad = \frac{\beta + \beta \quad + \quad + \beta}{+ \qquad \beta + \beta \quad + \quad + \beta}$$

π(x) refers to the probability of a success (in this case, the probability of receiving a Satisfactory rating) given the data available.

β_0, β_1, ..., β_k are the parameters of the equation that will be estimated in the following section.

$x_{1,}$, x_2, ..., x_k are the explanatory or independent variables (for the present study, these are the variables such as Classification or Out-of-Service Rate as defined in the previous section).

A transformation of the above equation, referred to as the logit transformation, gives the following result:

$$= \left[\frac{\pi}{-\pi}\right] = \beta + \beta \quad + \quad + \beta$$

One may notice that this equation appears similar to the regular linear regression model, and in fact, it does have many of the same properties (i.e., it is linear in the parameters and may be continuous).

Models Developed and Diagnostics - Preliminary Analysis (ND Data)

Since all of the above variables are considered to have some importance in the model, it was decided to fit the multiple variable model with every variable included. This first model revealed that although it appeared in the previous discussion that larger firms (more mileage) were significantly more likely to have a Satisfactory rating, the coefficient for this variable was not significant. This may be due to the fact that there is a difference between carriers with 5,000 annual miles and 500,000, but not between carriers with 5,000 and 6,000 annual miles. So, the mileage variable was changed into a categorical variable (small, medium, and large) as defined in the previous section. Small was used as the reference group, so the new model contains the variables MED and LARGE, as shown in Table 6.

For interpretation of the model, a positive coefficient (parameter estimate) indicates that as the variable *increases* (or if it is equal to one (1) if it is an indicator variable), the company is more likely to have a Satisfactory rating. Conversely, a negative coefficient indicates that as the variable *decreases* (or if it is equal to zero (0) if it is an indicator variable), the company is more likely to have a Satisfactory rating. Similarly, one can examine the odds ratio (which is simply obtained by exponentiating the coefficient). An odds ratio greater than one is interpreted the same as a positive coefficient, and an odds ratio less than one is interpreted the same as a negative coefficient as explained above. In addition, a further interpretation of the odds ratio may be as follows. A company that is Authorized-for-hire is 3.395 times more likely to have a

Satisfactory rating than one that is Exempt-for-hire and Private (the category used as the reference group). The other classifications are interpreted in the same manner.

Table 6. Multiple Variable Model (ND Data)

Variable	Parameter Estimate	Standard Error	Wald Chi-Square	Prob. > Chi-Square	Odds Ratio
Intercept	-1.0642	0.5408	3.8715	0.0491	0.345
CLA	1.2223	0.5883	4.3164	0.0377	3.395
CLE	0.7051	0.4594	2.3562	0.1248	2.024
CLP	0.5543	0.4587	1.4603	0.2269	1.741
CLAE	1.2145	0.4619	6.9154	0.0085	3.369
CLAP	2.4161	1.1979	4.0685	0.0437	11.203
CLAEP	0.8781	0.5367	2.6772	0.1018	2.406
MED	0.9930	0.4200	5.5890	0.0181	2.699
LARGE	1.1025	0.4780	5.3194	0.0211	3.012
DRVOOSRT	-2.1441	1.2809	2.8020	0.0941	0.117
VEHOOSRT	-1.1773	0.6227	3.5744	0.0587	0.308

An examination of this particular model indicates that each variable appears to enter the model as would be expected from the previous section. The classifications are all more likely than the reference classification to have Satisfactory ratings (positive coefficients), and the likelihood of a Satisfactory rating increases with an increase in mileage and increases with a decrease in driver or vehicle out-of-service rates.

All possible combinations of the above variables were introduced into the model to test for possible interactions. None of these were significant at the 0.05 level. Therefore, it was decided to continue to the diagnostics of the model to determine if any of the observations might be outliers (i.e., extreme observations) and/or influential points.

Several diagnostic measures, available from SAS statistical software through development by Pregibon (1981), were run. The first one examined was DIFDEV. This is defined in the SAS manual as "the change in deviance due to deleting an individual observation" and is useful for detecting observations that are not well fitted. A guideline given by Hosmer and Lemeshow (1989) is to examine more closely any observations with DIFDEV greater than four (4.0) as DIFDEV is distributed as chi-square with one (1) degree of freedom, and four (4.0) approximately corresponds with an alpha-level (significance level) of 0.05. None of the observations exceeded this approximation. However, a similar diagnostic, DIFCHISQ, which is the change in the sum of squares of the Pearson residuals from deleting an observation, reveals a couple of observations that warrant closer examination. Specifically, case numbers 203 and 269 have DIFCHISQ of 4.1922 and 4.3196, respectively.

Still another useful diagnostic measure is that of CBAR, which is defined in the SAS manual as a "confidence interval displacement diagnostic, which measures the overall change in the global regression estimates due to deleting an individual observation." Observations with larger than average CBAR values were numbers 275 and 276, with CBAR of 0.4265 and 0.8904, respectively.

A final common diagnostic measure given by SAS is the diagonal element of the HAT matrix, which is helpful in locating points in the design space that are extreme. One additional observation, other than those above, that had a larger HAT diagonal value is case number 266 with a value of 0.2548.

These five observations were examined more closely. Table 7 illustrates the five cases and their observed data, along with their estimated logistic probability and the above diagnostic statistics. The estimated logistic probability is obtained by plugging the appropriate values for the independent variables into the model from Table 6 and solving for $\pi(x)$.

Table 7. Diagnostic Measures and Data for Five Specific Cases

Case	Classi-fication	Size	VEH-OOSRT	DRV-OOSRT	Rat-ing	Estimated Prob.	DIF-CHISQ	C-BAR	HAT Diagonal
203	CLP	Sml	0.7500	0.0000	Sat	0.1989	4.1922	0.1661	0.0396
266	CLAP	Sml	0.2857	0.0000	Sat	0.7341	0.4860	0.1238	0.2548
269	CLP	Med	1.0000	0.3333	Sat	0.1964	4.3196	0.2286	0.0529
275	CLP	Med	0.0000	0.6667	Sat	0.2796	3.0025	0.4265	0.1421
276	CLAP	Sml	0.4286	0.0000	Not Sat	0.7000	3.2240	0.8904	0.2762

Examining the table, one sees three types of patterns apparent. First, case numbers 203 and 269 illustrate low leverage and poor fit (small HAT Diagonal, large DIFCHISQ). These observed outcomes are simply peculiar events, and exclusion of them would not significantly alter the parameter estimates of the model. Second, case number 266 is an example of high leverage and good fit (large HAT Diagonal, small CBAR and DIFCHISQ). The observed outcome is as would be expected by the model. The final pattern is demonstrated by case numbers 275 and 276, which show high leverage and poor fit (large HAT Diagonal, large CBAR and DIFCHISQ). One needs to consider exclusion of these observations and their effect on the model.

When observation 275 was excluded, some change was noticed in the DRVOOSRT parameter estimate, but little change in the rest of the estimates was observed. In addition, the -2 log-likelihood (a goodness of fit test for the model) changed very little. However, when observation 276 was excluded, again there was very little change in most of the estimates, but the CLAP parameter estimate was substantially larger. As before, however, the -2 log-likelihood was virtually unchanged. This suggests that exclusion of these observations would not result in any substantial improvement in the model. Additionally, there was no indication that the data were incorrect. Therefore, it was decided to make no further adjustment to the model.

Comprehensive Analysis (All Data)

The preliminary analysis above gives a good feel for the data and what to expect. The more comprehensive analysis now performed on all carriers in the data base will include models to predict both Satisfactory and Unsatisfactory ratings. As before, the variables used and their relationship to safety ratings are given for comparison with the North Dakota data.

Examination of Table 8 indicates that the carriers in the Authorized-for-hire category again have the highest percentage of Satisfactory ratings while those in the Exempt-for-hire and Private category have the lowest. Thus, the Exempt-for-hire and Private category will be used as the reference group (all the indicator variables equal to zero) in the model predicting probable Satisfactory ratings. Similarly, carriers in the Other category (not indicating any of the main three classifications - no North Dakota carriers fell in this category) have the highest percentage of Unsatisfactory ratings so this will be used as the reference group in the model predicting probable Unsatisfactory ratings. The variable names used in the models are as before with the one addition of CLO (Other).

Table 8. Classifications by Safety Rating Percentage (All Data)

Classification	Satisfactory Percentage	Conditional Percentage	Unsatisfactory Percentage
Authorized-for-hire (n=5,705)	65.89	23.79	10.32
Authorized-for-hire and Exempt-for-hire (n=319)	57.99	28.53	13.48
Authorized-for-hire and Private (n=229)	55.46	28.38	16.16
Authorized-for-hire, Exempt-for-hire, and Private (n=73)	49.32	36.99	13.70
Private (n=7,541)	45.54	34.94	19.52
Exempt-for-hire (n=1,231)	42.89	30.22	26.89
Other (n=151)	37.09	28.48	34.44
Exempt-for-hire and Private (n=149)	36.24	39.60	24.16

Table 9 below indicates that, like before, as the number of annual miles increases, there is a higher percentage of companies with Satisfactory ratings. The variable used in the models is MLPERMIL, which is simply the company's total mileage reported divided by one million (this variable is significant in the models developed in this section). This is done for ease of interpretation of the coefficient (parameter estimate).

Table 9. Annual Miles by Safety Rating Percentage (All Data)

Annual Mileage	Satisfactory Percentage	Conditional Percentage	Unsatisfactory Percentage
Less than 30,000 miles (n=1,376)	40.33	37.50	22.17
30,000 - 70,000 miles (n=2,351)	41.90	34.33	23.78
70,000 - 130,000 miles (n=3,018)	49.73	32.21	18.06
130,000 - 250,000 miles (n=2,844)	51.90	30.10	18.00
250,000 - 500,000 miles (n=2,590)	56.72	28.96	14.32
500,000 - 1,000,000 miles (n=1,645)	63.40	24.98	11.61
1,000,000 - 2,500,000 miles (n=1,074)	71.79	23.00	5.21
More than 2,500,000 miles (n=500)	75.80	18.00	6.20

Table 10 again shows a similar pattern as before, the first two categories are about equal and then there is a definite decreasing trend in the percent of Satisfactory ratings as the vehicle out-of-service rate increases. The variable used in the models is VEHOOSRT.

Table 10. Vehicle Out-of-Service Rate by Safety Rating Percentage (All Data)

Vehicle Out-of-Service Rate	Satisfactory Percentage	Conditional Percentage	Unsatisfactory Percentage
0.0 - 0.1 vehicle OOS rate (n=3,266)	54.35	31.26	14.39
0.1 - 0.2 vehicle OOS rate (n=1,988)	58.80	28.37	12.83
0.2 - 0.3 vehicle OOS rate (n=2,176)	58.00	27.53	14.48
0.3 - 0.4 vehicle OOS rate (n=3,196)	54.47	29.57	15.96
0.4 - 0.5 vehicle OOS rate (n=1,882)	50.96	30.98	18.07
0.5 - 0.6 vehicle OOS rate (n=845)	50.41	30.65	18.93
0.6 - 0.7 vehicle OOS rate (n=1,075)	44.84	31.35	23.81
0.7 - 0.8 vehicle OOS rate (n=546)	39.01	35.53	25.46
Greater than 0.8 vehicle OOS rate (n=424)	35.85	34.67	29.48

Table 11 demonstrates that the same trend is apparent as that for the vehicle out-of-service rates. The percent of Satisfactory ratings decreases as the out-of-service rate increases. The variable used for the models is DRVOOSRT.

Table 11. Driver Out-of-Service Rate by Safety Rating Percentage (All Data)

Driver Out-of-Service Rate	Satisfactory Percentage	Conditional Percentage	Unsatisfactory Percentage
0.0 - 0.1 driver OOS rate (n=10,298)	54.97	29.77	15.26
0.1 - 0.2 driver OOS rate (n=2,455)	55.52	29.53	14.95
0.2 - 0.3 driver OOS rate (n=1,122)	47.06	33.07	19.88
0.3 - 0.4 driver OOS rate (n=1,041)	43.13	31.80	25.07
0.4 - 0.5 driver OOS rate (n=248)	39.52	35.48	25.00
0.5 - 0.7 driver OOS rate (n=177)	37.29	28.81	33.90
Greater than 0.7 driver OOS rate (n=57)	24.56	29.82	45.61

With this in mind, the following models were developed. First, the case for ascertaining probable **Satisfactory** ratings is considered. Fitting all possible variables discussed above for this case yields the following model:

$$\text{Ln}\,\{\pi(x) / [1-\pi(x)]\} = -0.2307 - 0.7488(\text{VEHOOSRT}) - 1.3509(\text{DRVOOSRT}) + 0.0643(\text{CLO}) + 1.2404(\text{CLA}) + 0.2939(\text{CLE}) + 0.3764(\text{CLP}) + 0.8704(\text{CLAE}) + 0.7505(\text{CLAP}) + 0.5315(\text{CLAEP}) + 0.0514(\text{MLPERMIL})$$

This model provides good fit to the data with a p-value of 0.0001 and also provides reasonably good prediction ability with a coefficient of concordance of 0.640 (a value of zero would imply no prediction ability and a value of one implies perfect prediction). Again, in this model, $\pi(x)$ refers to the probability of obtaining a Satisfactory rating given the values of the independent variables. So, substituting values in for each of the variables and solving for $\pi(x)$ gives an approximate probability that a particular company should have a Satisfactory rating. The interpretation of the model is similar to what it was before.

Examining this particular model, one can see that those variables with positive coefficients are all the classification variables (as compared to the reference category of Exempt-for-hire and Private) and the annual miles variable. This means that carriers are more likely to have a Satisfactory rating as their annual mileage increases and if they are in any category except the Exempt-for-hire and Private one. The out-of-service rate variables have negative coefficients, indicating that companies are also more likely to have Satisfactory ratings as their out-of-service rates decrease. All of these conclusions correspond with what was expected from the previous discussion.

As an example, say one is able to determine that a company falls in the Authorized-for-hire category, has a vehicle out-of-service rate of 0.1, a driver out-of-service rate of 0.0, and has an annual mileage of 2,000,000. Substituting this information into the above model gives:

$$\text{Ln}\ \{\pi(x) / [1-\pi(x)]\} = -0.2307 - 0.7488(0.1) - 1.3509(0.0) + 0.0643(0) + 1.2404(1) + 0.2939(0) + 0.3764(0) + 0.8704(0) + 0.7505(0) + 0.5315(0) + 0.0514\ (2) = 1.03762$$

Solving the equation Ln $\{\pi(x) / [1-\pi(x)]\} = 1.03762$ for $\pi(x)$ gives $\pi(x) = 0.7384$ and this particular company has approximately a 73.84% probability that it should have a Satisfactory rating given the data. In this way, assigning a specific cutoff point for an acceptable probability (say, below 50.0%) would enable one to identify companies which are less likely to achieve a Satisfactory rating.

Next, the case for ascertaining probable **Unsatisfactory** ratings is considered. Fitting all variables once again gives the following model:

$$\text{Ln}\ \{\pi(x) / [1-\pi(x)]\} = -1.0457 + 0.9347(\text{VEHOOSRT}) + 1.4951(\text{DRVOOSRT}) - 1.4280(\text{CLA}) - 0.3422(\text{CLE}) - 0.7464(\text{CLP}) - 1.1065(\text{CLAE}) - 0.8700(\text{CLAP}) - 0.4991(\text{CLEP}) - 1.1463(\text{CLAEP}) - 0.3053(\text{MLPERMIL})$$

Again, this model provides good fit to the data with a p-value of 0.0001 and good prediction with a coefficient of concordance of 0.658. The model interpretation is the same as above. Notice that all the coefficients have changed sign, indicating that carriers are more likely to have Unsatisfactory ratings if they are in the Other classification (none of the seven defined), as their out-of-service rates increase, or as their annual miles decrease. Once again, this is as would be expected.

These models could be used in conjunction with each other to determine probable safety ratings of companies. For example, a carrier's characteristics could first be entered into the model to predict Unsatisfactory ratings. If they receive a probability lower than a certain cutoff point (aren't assigned an Unsatisfactory rating), they could then be entered into the model to predict Satisfactory ratings. Then, if they again receive a probability below the cutoff chosen (aren't assigned a Satisfactory rating), they are given a probable Conditional rating. In this way, carriers could be assigned probable ratings without conducting personal visits to them and carriers with higher than average probabilities of Unsatisfactory ratings could be targeted for review.

It is believed that information obtained from these models, together with any other information that the Federal Highway Administration may start requiring companies to submit, can quite accurately ascertain a likelihood of a safety rating. This would be very helpful in eliminating the majority of unnecessary visits to carriers and would allow concentration on firms with a high probability of not achieving Satisfactory ratings.

Further research that might be considered is developing similar models for each state or region of the country and comparing the results to the present models for differences. Separate analyses of bus companies and hazardous materials carriers might also be considered.

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