

IDENTIFYING DANGEROUS TRUCKING FIRMS

by

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ABSTRACT

The paper develops a statistical procedure for predicting the safety performance of motor carriers based on characteristics of firms and results of two government safety enforcement programs. One program is an audit of management safety practices, and the other is a program to inspect drivers and vehicles at the roadside for compliance with safety regulations. The technique can be used to provide safety regulators with an empirical approach to identify the most dangerous firms and provide a priority list of firms against which educational and enforcement actions should be initiated. The government needs to use such an approach rather than directly observing accident rates because the most dangerous firms are generally small and, despite relatively high accident rates, accidents remain rare events.

The technique uses negative-binomial regression procedures on a dataset of 20,000 firms. The definition of poor performance in roadside inspection is based on both the rate of inspections per fleet mile and the average number of violations found during an inspection. This choice was made because selection for inspection has both a random and nonrandom component.

The results of the study suggest that both of the government's safety programs help identify the most dangerous firms. The 2½% of firms that do poorly in both programs have an average accident rate twice that of the mean for all other firms.

Keywords: Trucks, Accidents, United States, Inspections

1. INTRODUCTION

The trucking industry in the United States was economically deregulated in 1980. However, the government still defines minimum acceptable levels of safety. The Federal Motor Carrier Safety Regulations (FMCSR) define driver qualifications, vehicle construction and condition, driving rules, and the maximum length of time that drivers can be on duty. The Federal Highway Administration (FHWA) has programs that are intended to (i) identify firms that fall below a minimum acceptable level of safety, and (ii) make those firms improve their safety performance or go out of business. This paper deals with the first of these objectives. In particular we wish to see whether two safety programs accurately identify the worst firms. One program is a system of roadside inspections, and the other program involves audits of the safety management practices of firms.

2. WHY DO WE NEED A PREDICTIVE TECHNIQUE?

One might imagine that knowledge of accident rates would be the only piece of information the FHWA needs in order to identify the most dangerous firms. The most dangerous trucking firms must be those with the highest accident rates. Unfortunately, there are severe data and methodological problems with such an approach.

Truck accidents occur much less frequently than one might be led to believe by the press and public opinion. A trucking firm with an accident rate three times the industry average has a reportable accident rate of 1½ accidents per million miles. The industry defines an accident as "reportable" if it involves a death, a serious injury or property damage severe enough that a tow-truck has to be called. Seventy percent of trucking firms operate less than 100,000 miles a year, so it is obvious that even potentially very dangerous firms could be in business for many years without having an accident. Previous analysis by the authors suggests that safety performance is worst among small firms [1].

There are also data collection problems. For many years accidents were self-reported, which most experts believe resulted in underreporting. However, the situation is improving because this information is now obtained from accident reports filed by attending police officers. There is also poor information on total miles logged by firms, which impedes calculation of accident rates. The government has good data for 40 percent of firms. Another 40 percent of firms self-report the number of trucks they own. The FHWA doesn't have any information on the remaining 20 percent of firms.

Therefore observation of accident rates in any given year, or even a series of years, is an unreliable way of identifying the most dangerous firms. The variability of accidents from year to year which is explained by a Poisson process could lead to type I and II errors in selecting firms for enforcement action if accident rates are the sole selection criteria. Consequently, the objective of this paper is to develop a predictive technique that is based on direct observation of the safety practices of firms, data that will not vary markedly from year to year.

3. ANALYTICAL METHOD

A regression model is used to explain the accident rates of 20,000 firms. Explanatory variables include physical characteristics of the firms, and also data on the performance of the firms in two government safety enforcement programs: audits of safety management practices; and inspection of drivers and vehicles at the roadside for compliance with safety regulations.

Statistical techniques were developed in the 1980s to deal with situations such as ours where the number of accidents that a firm has can only take non-negative integer values and follows a Poisson distribution [2,3]. They have been applied to accident data for airlines [4], shipping [5], and automobiles [6]. The estimated equation can be usefully visualized as having the form:

$$\text{count of accidents} = e^{(\Phi \ln(\text{exposure}) + \gamma \text{characteristics} + \delta \text{audit} + \theta \text{inspections})} + \varepsilon \quad (1)$$

Note that an accident rate is not used directly. The count of accidents is the dependent variable while exposure to accidents is an explanatory variable. While this formulation does restrict the relationship between accidents and exposure to one that can only slope in a single direction and has a constant elasticity, previous analysis has found that this formulation fits truck accident data well [1]. A statistical test of the value of Φ can determine whether accident rates appear to be invariant with firm size ($\Phi = 1$), increase with firm size ($\Phi > 1$), or decline with firm size ($\Phi < 1$).

The statistical procedure assumes that the count of accidents for any individual firm follows a Poisson distribution. The Poisson distribution for any firm is characterized by a parameter λ_i which represents both the mean number of accidents (the dependent variable) and its variance. The statistical technique estimates the λ_i 's based on the explanatory variables in the regression. Problems can emerge with the error structure of an estimated regression when it does not contain every variable that explains the different λ_i s across firms. Given the low likelihood that one is ever able to fully account for the idiosyncratic differences between firms, both we and other researchers have used a modified regression technique called the negative binomial. This estimation technique assumes that the error term is distributed according to a gamma distribution.

There is a whole family of negative binomial distributions, which vary according to the assumed relationship between the mean and variance of the standard error of the dependent variable. Which particular assumption is employed is an empirical matter based on tests of goodness of fit. Our earlier investigations of truck accidents [1] led us to prefer the negative binomial II regression model. This model assumes that the mean ($E(y)$) and variance ($\text{Var}(y)$) of the count of accidents for a group of firms with identical values of the explanatory variables have the following relationship:

$$\text{Var}(y) = E(y) + \alpha E(y)^2 \quad (2)$$

The use of a squared term is the source of the "II" in the name of our preferred model. Note that if $\alpha = 0$ the equation becomes the standard Poisson condition. The statistical package used

(LIMDEP) reports the estimated value and standard error of α . Standard statistical tests can be conducted to see whether or not the Poisson assumption is appropriate.

Problems can also arise with Poisson variables if nearly all the observations of the dependent variable are zero. Fortunately, the dataset used in this analysis is so large that there are over 3,500 firms with non-zero accidents. Therefore statistically significant relationships can be identified.

4. VARIABLES AND DATA

4.1 Accidents, Exposure, and Characteristics

The data on reportable accidents, mileages and characteristics are collected during safety audits. Accidents and mileages pertain to the 365 days prior to the audit. Exposure to accidents is measured by fleet mileage. In addition, five explanatory variables are employed that represent physical characteristics of firms. The choice of these characteristics is based on experience gained from several years of working with this database. The first is a dummy variable for private carriers. These are trucking firms that are owned by manufacturing or service companies and primarily carry the goods of their parent organizations. The next is the proportion of drivers employed in trips over 100 miles, which is a measure of the mix of short distance and long distance operations by the firm. The accident experience of urban operations may well be different from those operations on the open highway.

The final three characteristics are dummy variables that indicate the type of goods hauled. Our previous experience is that certain segments of the industry have quite distinct accident performance. The three categories used are: general freight, which is to say the firm does not specialize in any one commodity; agricultural goods, which include forest products, livestock, fresh produce, grain, feed and hay; and hazardous materials. The final category includes all carriers that transport any quantity of any cargo defined as "hazardous" by the government.

4.2 Safety Audit

The first of the two enforcement programs which we will use to provide data to predict safety performance is a system of safety audits. In this program, government inspectors visit the operating bases of firms and question managers about safety-related procedures and policies such as those governing maintenance of vehicles, and driver hiring and training. They do not actually inspect any equipment or test drivers. They mark "yes" or "no" answers to 75 questions [7]. The questions are grouped into five categories called "rating factors": general, driver, operational, vehicle, and hazardous materials handling.

Each question is assigned a severity weighting between 0 and 10. Within each of the five categories the FHWA tallies the number of penalty points derived by multiplying "no" answers by the severity weighting. Firms are then rated as satisfactory, conditional, or unsatisfactory in each of these five rating factors. The government also uses the previous year's accident rate as a sixth rating factor, although it makes allowance for the fact that the rarity of

truck accidents makes this factor a dubious guide for all but the largest 10% of firms. Clearly the incorporation of this sixth rating factor would compromise the use of the audits as an explanatory variable in our regressions because of endogeneity.

Therefore, the audit variable used in our regressions is based solely on the first five rating factors which are derived from the objective, factual questions asked by inspectors. Using the FHWA formula [8] a firm is assigned an unsatisfactory overall rating if it is judged to be unsatisfactory in two or more of the five rating factors, or receives one unsatisfactory factor rating and more than two conditional factor ratings. In this paper, a single dummy variable is used to represent an unsatisfactory overall rating, which is assessed against about 10 percent of firms. Experience has shown that use of the ratings on individual questions and / or sections of the audits is a less effective way of identifying the worst firms [1].

4.3 Roadside Inspections

The second enforcement program is a system of inspections of vehicles and drivers at the roadside. Over 1½ million trucks are inspected each year. Many are conducted at existing weigh stations where all trucks are required to stop when stations are open. Other vehicles are pulled over by specialist officers who patrol in cars. A uniform inspection procedure is employed throughout the United States and Canada. Officers walk around and look under the vehicle and check the brakes. They also check whether drivers possess correct licenses, and have adhered to the maximum number of hours a driver can operate legally without rest, as revealed in the log drivers are required to keep. Officers also judge whether drivers are under the influence of alcohol or drugs.

If serious faults are found the vehicle and/or the driver can be placed "out of service." In general, vehicle faults have to be corrected at the site of the inspection. Drivers are also kept out of service at the inspection site until they are no longer impaired or are back in compliance with hours-of-service regulations.

The paper concentrates on data for vehicles rather than data for drivers. We do so because problems are found with vehicles five times more frequently than they are with drivers. The widespread falsification of log books makes detection of hours-of-service offenses difficult. Therefore, data on vehicle violations display more variability and have fewer firms with zero violations. For each firm the number of roadside inspections in 1991-92, and the number of vehicle out-of-service violations issued is known. Vehicles can be assessed more than one out-of-service violation as a result of an inspection if they have multiple mechanical problems. The measure we employ in our regression is total violations divided by total inspections. Our reason for this choice is our belief that in general a vehicle that has multiple violations poses a more serious threat to safety than one with a single violation.

If vehicles were inspected randomly, there would be a very simple rule for interpreting inspection data. The higher the proportion of out-of-service violations to inspections, the worse the firm. However, this simple rule breaks down when selection of vehicles for inspection is nonrandom. The FHWA admits that roadside inspections are not designed to be a random sampling of the nation's truck fleet. The goal of inspections is to enforce Federal Motor Carrier

Safety Regulations. The FHWA says that "[in] most states [officers] tend to select vehicles for inspection based upon judgmental factors such as appearance and physical condition, which leads to a higher likelihood of noncompliance with safety requirements" [9].

The above comments are not to be taken as a criticism of the officers. Their time is limited, and their objective is to remove bad vehicles and drivers from the road. Problems emerge when inspection data are used for secondary purposes such as the predictive equation discussed in this paper.

The authors used field interviews with specialist motor-carrier officers from the Illinois State Police to investigate inspection strategies. The officers said that about 60% of their inspections are purely random. They are concerned with making the best use of their duty time, and felt that even the most reputable large firms should be checked occasionally to "keep them honest." Officers have a quota of inspections to conduct in a month and cannot wait around for a bad truck to appear. The other 40% of inspections are "with cause." The poor external condition of vehicles, including visible mechanical components, raise officers' suspicions that violations may be present. The officers also know by experience to target specific bad firms or bad categories of firms (e.g., gravel haulers). While the ratio of random to "with cause" inspections does vary from officer to officer and from state to state, it is clear that truck companies are open to both types of inspections.

If inspections were purely random, the inspection rate would be constant for all firms and the violation rate would be a reflection of the maintenance practices of firms. When inspections are "with cause," the violation rate should be roughly constant across firms because vehicles are almost certain to be assessed a violation, but the maintenance practices of the firm will strongly influence the rate at which vehicles are stopped for inspection. Therefore, both the inspection rate and the violation rate should be used as explanatory variables in a regression.

4.4 Data Source

The data for the analysis was downloaded from the FHWA's Motor Carrier Management Information System (MCMIS) in January 1993. To assure that our data were relatively recent we required that firms had received a safety management audit after January 1990, and also had at least one roadside inspection in the twenty-four-month period 1991-92. We also set a minimum for annual fleet miles of 20,000, which is not much more than the mileage of many family automobiles. About 10% of trucking firms operate less than 20,000 miles a year. They are primarily in urban delivery operations or in rural farming, mining or forestry. Since the roadside inspection program occurs primarily on limited-access highways these firms are rarely inspected.

The dataset comprised 19,589 firms. It represents about 8 percent of all trucking firms and 20 percent of firms that have ever had an audit. On average, a truck is subject to a roadside inspection once every five years. Therefore it is not surprising that smaller firms who own six or fewer trucks are proportionately underrepresented in the dataset. However, there is no reason to believe that we have a serious selectivity bias in the sample because our dataset only contains "bad firms." The FHWA has a mandate to audit all trucking firms, and every firm is

open to inspection in the random roadside inspections. Eighty percent of audits result in a conditional or satisfactory rating. Of the 1½ million inspections conducted a year, 70 percent of vehicles and over 90 percent of drivers are found to comply with safety laws. Approximately 70% of the firms in our sample do not have a poor record on either of the safety programs.

Descriptive statistics of the variables used in the regression analysis are shown in table I.

5. REGRESSION RESULTS

Three regressions are reported in table II. Regression I has only firm characteristics variables; regression II has characteristics and roadside inspections results; and regression III contains characteristics, roadside inspection results and audit ratings. The addition of each body of information leads to improvements in log likelihood that are significant at the 1% level. The highly significant α coefficient in all equations permits us to reject the Poisson assumption and prefer the negative-binomial formulation.

Many of the results support the conclusions of earlier research [1]. Private carriers have consistently been found to have 20 percent lower accident rates than comparable for-hire carriers. It may be that these firms have strong incentives for safe operation since it is the company's own cargo that would be damaged in an accident. Private carriers also have the advantage of relatively repetitive operations, which means that drivers are more familiar with specific routes and local hazards.

Our earlier papers found a strong negative relationship between firm size, as measured by fleet miles, and safety performance. This continues to be true in regression I which contains only firm characteristics. However, the addition of the roadside inspection variables first and then the audits removes this effect. This is a good result in that it implies that audit and inspection variables are correctly identifying the poorer than average maintenance and safety management practices common among smaller firms. Smaller firms are inspected very frequently at the roadside. The audit program assigns an unsatisfactory rating to somewhat more than 15% of smaller firms. That proportion falls to less than 2% for the largest firms.

While the difference in reportable accident rates between short-distance and long-distance firms is statistical significant, the magnitude of the difference is small. In the regression that contains characteristics only, an exclusively long-distance firm has a 5% lower accident rate than a comparable firm that operates short distances exclusively. Compared to rural areas, congested urban areas have higher accident rates for all types of accidents, but they are typically less severe.

The present dataset reveals that agricultural carriers have an accident rate 8 percent above that of other carriers. General freight and hazardous materials firms are not statistically different from other firms.

The variables derived from the federal programs produce strong results. The 1,907 firms, or about 10 percent of firms, rated unsatisfactory on a safety audit have significantly

higher accident rates. The model suggests that their accident rates are 46 percent higher than comparable firms rated conditional or satisfactory.

The roadside inspection rate takes a very strong positive sign which reflects the predictive power of the number of "with cause" inspections. The model suggests that a firm with 40 inspections per million miles (approximately one standard deviation above the mean) has an accident rate 17% above that of a firm with 4 inspections per million miles (which is approximately one standard deviation below the mean).

A higher rate of violations per roadside inspection, a measure of performance in random inspections, is associated with higher accident rates. The model suggests that a firm with a violation rate of 1.7 (approximately one standard deviation above the mean) has an accident rate 10% above that of a firm with a violation rate of 0.2 (which is approximately one standard deviation below the mean). Of course, a firm with poor maintenance should do badly in both random and "with cause" inspections. A firm with a poor overall record in roadside inspections is predicted to have about a 30% worse accident rate than one that does well.

6. AUDITS AND INSPECTIONS: SUBSTITUTES OR COMPLEMENTS?

From a policy point of view, it is important to ask whether the two government safety programs simply identify the same poor firms and are therefore wastefully duplicate each other, or whether they work in tandem and complement each other. The results in table 2 suggest that the latter is the case. The introduction of inspections and audits variables produces both statistically significant coefficients and improvements in log likelihood that comfortably pass likelihood-ratio tests. Each program produces new information which improves the predictive powers of the model.

This finding can be supported visually by using Venn diagrams. For illustrative purposes, three important determinants of accident performance have been selected to define groups of firms. The first is the most powerful of the firm characteristic variables, the distinction between private and for-hire carriers. Approximately, 45 percent of firms are for-hire. The second is the 10 percent of firms rated unsatisfactory in an audit. The third is firms with poor performance on roadside inspections. For the purposes of these diagrams, we defined this last group as the 26 percent of firms that have a greater than mean inspection rate and a greater than mean violation rate.

Figure I has a Venn diagram which assumes that the government only knows characteristics and roadside inspections results. Figure II introduces audit results. Within each segment of the diagrams the average reportable accident rate per million miles is shown. The number of firms in that segment is in parentheses. Figure I clearly shows that poor roadside inspection results are a strong indicator of poor accident performance. The introduction of information from audits has the powerful effect of isolating the seemingly worst 10 percent of the firms with poor roadside inspections. The 518 firms that have both an unsatisfactory audit and a poor inspection record have an accident rate of 1.15 per million miles. This number is twice the accident rate of all other firms.

The fact that the average accident rate of the group of 518 poor firms is "only" twice that of other firms may strike some readers as surprisingly small. Albeit, that the difference is highly significant statistically with a t-statistic of 4½. However, readers should remember that our data measures the most serious accidents, and that each year the worse than average accident rates of the 518 poor firms result in 5 additional fatalities and 50 additional serious injuries, based on typical accident severity data for the industry.

With information from both programs, the government can identify a manageable group of firms on which to concentrate its enforcement and educational activities. It is clear that the audit program reinforces the information from the roadside inspection program, but neither program is a complete substitute for the other. A combination of poor roadside inspection results and firm characteristics can be used in deciding on a priority list of firms to audit.

It is worth observing who the very poor 518 firms are. They are primarily small firms. The median size is about half that of all other firms. They operate 63,000 annual fleet miles compared with 118,000 miles for other firms. Because the distribution of truck firm sizes is heavily skewed to the left, and none of the extremely large firms have poor audits or roadside inspection records, the comparison of mean sizes is starker. The average annual fleet miles for the 518 firms is 157,000 miles compared with 1.3 million miles for other firms.

The relatively small size of the most dangerous firms reinforces our earlier point that audits and inspections are a better guide to safety performance than accident rates. With an accident rate of 1.15 accidents per million miles, a median sized poor firm can be expected to have a reportable accident once every 14 years, and an average size poor firm once every 5½ years! Indeed, 442 of the 518 potentially most dangerous firms did not have a reportable accident in the year prior to their audit.

7. IMPLICATIONS

The government is aware of the general characteristics of about 80% of the firms in the industry. The roadside inspection program provides the government with information for about half of the interstate portion of the industry in a two-year period. The research of this paper suggests that a priority index of firms to audit can be derived from our estimated equation number II which contains certain firm characteristics and measures of poor performance in roadside inspections. A priority ranking of firms to audit is essential because while the audit is the most powerful weapon in the FHWA's arsenal, it is time consuming and resources are only available to audit relatively few firms in any year.

The relatively small number of firms which do poorly in both roadside inspections and audits are found to have accident rates significantly higher than those of other firms. These are the firms that the government should target with legal sanctions, educational advice, and in the extreme revocation of operating licenses.

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TABLE I: DESCRIPTIVE STATISTICS

VARIABLE	TYPE OF VARIABLE	SAMPLE MEAN	STANDARD DEVIATION
Count of Accidents	Integer	0.75	7.33
Fleet Miles (millions)	Continuous	1.27	11.53
Private Carrier	Binary	0.56	-
General Freight Hauler	Binary	0.15	-
Agricultural Goods Hauler	Binary	0.28	-
Hazardous Materials Hauler	Binary	0.23	-
Percent of Drivers Operating over 100 miles from Home Base	Continuous	0.68	0.47
Unsatisfactory Safety Audit Rating	Binary	0.10	-
Roadside Inspections per Million Miles (weighted by miles)	Continuous	8.86	10.52
Vehicle Out-of-Service Violations per Inspection (weighted by miles)	Continuous	0.61	0.45

TABLE II: NEGATIVE BINOMIAL REGRESSIONS ON REPORTABLE ACCIDENTS

REGRESSOR	COEFFICIENT (t-RATIO)		
	I	II	III
Constant	-13.789 (102.7)	-14.119 (99.7)	-14.248 (98.0)
Log of Fleet Miles [<i>This coefficient is compared with 1 for the t-ratio</i>]	0.966 (3.71)	0.983 (1.84)	0.990 (1.01)
Private Carrier	-0.212 (6.05)	-0.189 (5.34)	-0.191 (5.39)
General Freight Hauler	0.017 (0.45)	0.004 (0.10)	0.007 (0.18)
Agricultural Goods Hauler	0.075 (2.36)	0.080 (2.50)	0.077 (2.40)
Hazardous Materials Hauler	0.011 (0.35)	0.007 (0.23)	0.014 (0.43)
Percent of Drivers Operating over 100 miles from Home Base	-0.058 (1.72)	-0.073 (2.17)	-0.067 (1.98)
Roadside Inspections per Million Miles	-	0.004 (11.8)	0.004 (11.8)
Vehicle Out-of-Service Violations per Inspection	-	0.069 (2.85)	0.063 (2.57)
Unsatisfactory Safety Audit Rating	-	-	0.381 (5.44)
α (Over-dispersion Parameter)	0.412 (19.9)	0.400 (19.7)	0.398 (19.7)
Log-Likelihood	-11,093	-11,066	-11,053
p of likelihood-ratio test	>0.995*	>0.995	0.995
Number of Observations	19,589		

* comparison is made with an equation with a constant and log of miles only which has a log-likelihood of -11,118

FIGURE 1: FOR HIRE CHARACTERISTIC AND ROADSIDE INSPECTION PERFORMANCE



FIGURE 2: SAFETY AUDIT INFORMATION ADDED

