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Predicting Truck Crash Involvement: Developing a Commercial Driver Behavior Model and Requisite Enforcement Countermeasures



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ABSTRACT

Trucking-related safety metric trends have generally improved over the last 10 years, with the truck-related fatality rate dropping to its lowest level on record in 2003. However, neither industry nor FMCSA have yet reached their safety metric targets of 1.5 fatalities per million miles driven. It is becoming more challenging to identify new tools and programs that can further achieve the desired and incremental safety improvements.

Recognizing the role that driver risk factors can play in future safety events, the American Transportation Research Institute (ATRI) undertook research to identify an overall driver performance-based model for predicting future crash involvement. The model is based on truck drivers' historical driving record data. ATRI's research team included North Dakota State University Upper Great Plains Transportation Institute (NDSU/UGPTI) and the Commercial Vehicle Safety Alliance (CVSA).

The research team accessed and analyzed several available subsets of driver-specific data to design and test the model. The model includes specific violations discovered during roadside inspections, driver traffic conviction information and past accident involvement. A secondary component of the research identifies effective enforcement actions to counteract the identified problem driving behaviors/events.

The analysis shows that eight moving violations (i.e. citations) were significant with an associated crash likelihood increase between 21 and 325 percent. Four driver violations were associated with a crash likelihood increase between 18 and 56 percent. Twelve convictions were significant with an associated crash likelihood increase between 24 and 100 percent. Furthermore, drivers who had a past crash increase their likelihood of a future crash by 87 percent.

According to the states identified as having more traffic enforcement and lower crashes, successful enforcement strategies for addressing problem driver behaviors are those that exhibit one or more of the following components: creating aggressive driving apprehension programs/initiatives; focusing on both CMV and non-CMV driver behavior patterns; conducting highly visible enforcement activities; using a performance-based approach to identifying specific crash types, driver behaviors and locations; and conducting covert enforcement activities. As an example, Washington State has an enforcement approach that integrates these activities into a holistic program.

INTRODUCTION

The trucking industry in general has worked closely with government agencies to reduce the number of truck-related fatalities. These efforts have not been in vain; the U.S. Department of Transportation (USDOT) recently reported that the fatal crash rate for large trucks has decreased from 2.2 fatalities per 100M vehicle miles traveled (VMT) in 2002 to 1.9 fatal crashes per 100M VMT in 2003 (1,2). Preliminary data for 2003 shows further decreases in the truck fatality rate.

However, as the fatality rate decreases, it becomes more challenging to develop and formalize meaningful safety initiatives. In recognition of the continuing need to seek out ways to reduce large truck crash involvement, the American Transportation Research Institute (ATRI) recommended as part of its 2003 Research Agenda the development of a truck driver behavior-based predictive model for future crash involvement.

Identifying those driver behaviors and/or events that are most likely to lead to future crash involvement would provide carriers with appropriate training strategies, and law enforcement with the basis for enforcement actions that target the behaviors that underlie crashes.

BACKGROUND

There were approximately 416,183 truck crashes in 2002 that resulted in fatalities, injuries and/or property damage (2). The highest grouping of truck crashes involved another moving vehicle, with collisions with a fixed object as the second most frequent “first harmful” event. The truck crashes can be grouped by event into the following categories:

- ❑ fatal crashes – 4,183;
- ❑ injury crashes – 90,000; and
- ❑ property damage crashes – 322,000.

There have been several noteworthy trends related to fatal, injury, and property damage only (PDO) crashes over the last several decades. Fatal crashes and injury crashes have generally been in decline since 1979. Injury crashes have seen more fluctuation over time than the fatal crashes. PDO crashes have been erratic over time without a discernible trend. During this same time period, the number of vehicle miles traveled (VMT) has increased and the number of heavy vehicles on the road has likewise increased significantly. It is also well documented that congestion has increased significantly during this time. It is not surprising then, given the increase in VMTs, that the fatal, injury and property damage crash rates (per million VMT) have generally decreased over the last 20 years.

Fatal crashes peaked at 5,684 with year-to-year fluctuations. The reduction in the number of fatal crashes, coupled with the increase in vehicle miles traveled has resulted in a steady decline in fatal crashes per 100 million vehicle miles from 1979 to 2002. Although this is certainly a sign of improvement, there were still 4,897 fatalities resulting from large truck

crashes in 2002, with slight increases in 2003 figures. Injuries resulting from crashes displayed a similar trend.

A peak of 106,000 injury crashes were observed in 1989, a low of 75,000 injury crashes in 1991, and a total of 90,000 injury crashes in 2002. Injury crashes per 100 million vehicle miles showed a strong downward trend, peaking in 1989 at 74.6 and leveling off in 2001 and 2002 at approximately 40 injury crashes per 100 million vehicle miles. As with fatal crashes, this crash reduction was concurrent with substantial increases in total truck VMTs.

The largest recorded number of Property Damage Only (PDO) crashes took place in 1999 at 353,000. The trend for the number of PDO crashes per 100 million miles traveled is similar to fatal and injury crashes with a general decline over time interrupted by occasional upward spikes.

While progress has been realized, more work is needed. A study conducted by the National Highway Traffic Safety Administration (NHTSA) concluded that the total economic cost of *all motor* vehicle crashes in 2000 amounted to \$230.6 billion, 2.3 percent of the U.S. Gross Domestic Product (GDP) (4). The costs include productivity losses, property damage, medical costs, rehabilitation costs, travel delay, legal/court costs, emergency services, insurance administration costs, and costs to employers. These costs were based on 41,821 fatalities, 5.3 million non-fatal injuries and 28 million damaged vehicles.

Although these costs are aggregated for all motor vehicle crashes, they may provide insight into heavy truck crash costs. Based on the findings of the study, the fatal crash costs in 2000 dollars were \$1,092,464 per crash, injury crash costs were \$45,931 per crash, and PDO crash costs were \$4,437 per crash (4). Since heavy truck crashes are more costly than the average for all vehicles because of the size and weight of trucks, for purposes of this study these figures will be used as estimated minimum heavy-truck crash costs. Based on these estimates the total annual cost of heavy truck crashes in 2000 would be \$10.9 billion. Although significant, this figure is significantly less than the \$230.6 billion total cost estimate for all crashes.

In an effort to recalibrate these estimates for the increased severity of truck crash costs, the authors reference a study conducted by the Office of Research and Technology, Federal Motor Carrier Safety Administration (5). That study concluded that the average cost in 1999 dollars of large truck crashes was \$11,299 for a PDO crash, \$217,005 for an injury crash, and \$3,419,202 for a fatal crash (6). These estimates are a magnitude of two to three times higher than the average for all crash costs developed in the NHTSA study. Relating FMCSA cost data to crash statistics produces a total for heavy truck crashes in 2000 at \$40.3 billion.

From a crash causation standpoint, it is important to note that a preponderance of government and industry research indicates that, in multi-vehicle truck crashes, the non-truck vehicle is at primarily faulted. When the truck crash does not include another vehicle, preliminary results from the current FMCSA / NHTSA Large Truck Crash Causation Study reveal that the critical reason for single-vehicle CMV crashes is “driver-related” in two-thirds of the cases (7). Therefore, to have the most profound impact on the number of crashes, greater attention must be focused on the driver.

PREVIOUS RESEARCH

There have been several previous studies that have utilized commercial driver information for analysis to gain a stronger understanding of driver factors related to CMV crash rates. These studies provide insight into the driver-based performance factors to examine in the current study.

Carrier-Based

One of the initial studies that linked commercial driver information to the carriers that employ them was the Driver/Carrier Data Relationship Project. This study examined 1994 traffic citation data from two states, Indiana and Michigan. In most states, when a commercial motor vehicle driver is given a traffic citation, the employing motor carrier is not identified on the citation. However, the state police in these two states do try to identify the employing motor carrier, and note it on the traffic citation. Thus, driver citation data was able to be linked to the employing motor carrier for this analysis. The main conclusions from this study were that driver citation rates significantly differ among carriers, and that higher driver citation rates for a carrier are also associated with higher accident rates for that carrier (8).

The University of North Carolina also conducted research examining North Carolina carrier data that revealed that "serious driving violations" were a strong predictor of crashes. Once again, the analysis was conducted at the carrier level and the study focused on the relationship between drivers' violations and carrier crash rates (9).

Unfortunately, there is no national traffic citation database, nor any standard among state databases. In addition, there are only a few states which record the U.S. Department of Transportation (DOT) carrier number on traffic citations, and these states have issues with state or local police officers accurately identifying the employing motor carrier when issuing a traffic citation. Thus, it is not currently feasible to use citation data nationwide to identify higher risk motor carriers.

An additional carrier-driver-conviction data (CDC) study concluded that linking driver conviction data from the CDLIS to the employing motor carrier provides an additional method to identify those motor carrier companies with safety problems. A carrier-driver-conviction measure was created based on the average number of traffic convictions of drivers associated with carriers is significantly correlated with the carriers' out-of-service (OOS) rates, crash rates, and SafeStat Safety Evaluation Area (SEA) scores. Carriers with higher (worse) driver conviction measures are also more likely to have higher OOS rates, crash rates, and SEA scores (10).

Building on the CDC study, a project is currently underway to examine the addition of this carrier-driver-conviction measure into the roadside Inspection Selection System (ISS) that is in use by roadside inspectors nationwide. The ISS is used to help identify which vehicles and drivers to inspect based on prior carrier safety history (11). The majority of this recent work has been conducted by Ms. Brenda Lantz of North Dakota State University.

Driver-Based

Prior research conducted by the Virginia Tech Transportation Institute has identified that “commercial drivers differ greatly in their levels of crash risk, and that a relatively small percentage of drivers (10-15 percent) account for a disproportionate percentage of total fleet risk (30-50 percent).”(12) Given this, future research should begin to focus more on the driver-level rather than the carrier-level. To date, very little research has taken this approach.

PROJECT DESCRIPTION

The first research goal was to design and test an algorithm for predicting future crash involvement based on prior driver history information. A second component of the research, conducted in conjunction with the Commercial Vehicle Safety Alliance (CVSA), was to identify effective enforcement actions to counteract the driving behaviors and events that are predictive of future crash involvement. Data sources for this study include MCMIS and CDLIS.

FMCSA maintains a centralized database of carrier-based information regarding accidents and roadside inspections of commercial motor vehicles and drivers (MCMIS). This information is entered by states into their local SAFETYNET information system. The states then transmit relevant data for carriers electronically to MCMIS. Most accident and roadside inspection reports in MCMIS identify both the driver and the motor carrier the driver was working for at the time. There are approximately three million roadside inspections and 100,000 accidents reported each year. MCMIS also contains census information regarding each motor carrier (i.e., address, number of power units, number of drivers, cargo carried, etc.).

CDLIS was created in response to the Commercial Motor Vehicle Safety Act (CMVSA) of 1986. It is the only existing nationwide source of commercial driver’s license (CDL) drivers’ traffic conviction data. CDLIS is a distributed, relational database that provides a linkage between the various state driver records systems using a central index. CDLIS has been in full operation since April 1992. The central index serves as a clearinghouse that each of the 51 jurisdictions (the 50 states and the District of Columbia) can check before issuing a CDL to ensure that no other state has issued a CDL to that driver, and that the records for that driver’s CDL will be transferred to the new state where the driver is applying. It also assists states in reporting out-of-state convictions to the licensing state where they are made part of the driver’s record.

METHODOLOGY

Task 1: Data Analysis

The hypothesis for this study is that an overall driver performance-based indicator, which will provide predictive capabilities, can be developed. The indicator was developed based on correlational analysis of key driver behaviors. In addition, research questions focused on specific types of driver violations or convictions that are more highly correlated with future crash involvement. If proven, are there particular enforcement actions that could be effective in counteracting these behaviors and events?

The main dependent variable is crash involvement. For this study, crash involvement is the objective measure of driver “safety.” The independent variables for this study are driver-specific performance indicators mined from available data. Performance indicators include specific violations discovered during roadside inspections; driver traffic conviction information; as well as any past accident involvement information.

The study design is longitudinal to support trend analyses and predictive modeling. Driver data was gathered across a several-year time frame, and was analyzed across years to determine future crash predictability. For each of the drivers in the sample selected, their history regarding past inspections and crashes is available through MCMIS, and their history regarding past convictions is available through the CDLIS. Descriptive statistics were run for this entire dataset to determine subsets of the sample for analyses.

Appropriate statistical tests, including Chi-Square analyses, were used to assess whether there is a significant difference in future crash rates for drivers based on past inspection, conviction, and/or crash information. The data processing was conducted both in an aggregate manner, as well as for specific violations and convictions, and state-by-state.

Logistic regression is used to analyze a predictive model with a non-continuous dependent variable. In the present study, the dependent variable is the prior crash status of each driver. Logistic regression is a relatively new procedure that has been most utilized in the last 20-25 years with the advancements in technology and available software. 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.

The exact general form of the logistic regression model is:

$$y = \exp(b_0 + b_1*x_1 + \dots + b_n*x_n) / \{1 + \exp(b_0 + b_1*x_1 + \dots + b_n*x_n)\}$$

where y refers to the probability of a crash, b_0, b_1, \dots, b_n are the parameters of the equation that will be estimated, and x_1, x_2, \dots, x_n are the explanatory or independent variables.

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

$$\ln \{y/(1-y)\} = b_0 + b_1*x_1 + b_2*x_2 + \dots + b_n*x_n$$

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).

Task 2: Relating Data Analysis to Effective Enforcement Countermeasures

Early in the study it was determined that a performance metric would be needed to relate safety statistics to enforcement strategies on a state-by-state basis. An objective performance

measure was created that statistically related the amount of CMV traffic enforcement within each state to the number of crashes that occurred within each state. This performance metric assumes that there is a relationship between the level of CMV traffic enforcement and the number of crashes within each state. Once this analysis, which was conducted for all 51 U.S. jurisdictions including the District of Columbia, was completed, state performance tiers were developed.

In order to identify those states that conducted the highest level of enforcement, the research team divided the number of inspections with traffic enforcement for each state by the national total for this time period and dataset. In order to identify which states had the fewest crashes, the research team divided the number of crashes in the state by the national total for this time period and dataset to come up with a percent of total crashes which occurred in each state. In order to identify which states had the highest enforcement and lowest crashes, the research team then subtracted the percent of crashes from the percent of enforcement to get the point difference between the two to provide a way to sort the states and identify which states have more enforcement and lower crashes. This methodology was used due to the limited existence of needed data sets and as an attempt to not merely look at enforcement but to also develop an impact measure. The research team also calculated the ratio of crashes to inspections with traffic enforcement in each state. The breakdown of states is consistent with the methodology mentioned above.

Task 3: Identifying Effective Enforcement Countermeasures

The state baseline survey was distributed to 51 enforcement jurisdictions with the primary objective of developing a compendium of activities currently being conducted by enforcement agencies. The survey was designed to identify how enforcement agencies address overall CMV driver behavior and performance issues. The first section of the survey focused on the enforcement capabilities of CMV enforcement personnel while the remaining questions attempted to elucidate specific information regarding the extent of their jurisdiction's implementation of enforcement programs/initiatives and their level of internal analysis.

A targeted survey was later distributed to those states that were identified in Task 2 as being states that had a higher level of CMV traffic enforcement and lower level of crashes. The primary purpose of the survey was to identify preliminary enforcement strategies and best practices among states that appear to be proactive in conducting traffic enforcement and achieving positive results. The first two questions on this survey focused on ranking effective enforcement strategies and best practices previously identified in the baseline survey, followed by three additional questions designed to elicit more detailed information regarding effective enforcement programs/initiatives within each jurisdiction.

As a final task relating to enforcement strategies, the research team completed a series of in-depth interviews with the states that ranked in the top tier in the initial state analysis in order to provide additional clarification on the identified effective enforcement countermeasures.

RESEARCH FINDINGS

Task 1: Data Analysis

The first step initially identified the driver sample that had received a roadside inspection in February, March and/or April 2004. This yielded a population of 586,894 unique drivers. Of these, 540,750 drivers were U.S. drivers (these are the only drivers for whom traffic conviction information was accessible).

Between February 1, 2001 and April 30, 2004, the 586,894 drivers had 46,100 crashes reported to FMCSA.

- ❑ 1,633 crashes resulted in one or more fatalities;
- ❑ 20,598 crashes resulted in one or more injuries; and
- ❑ 41,591 crashes resulted in one or more vehicles towed from the scene.

The 586,894 drivers had a total of 2,213,551 roadside inspections between February 1, 2001 and April 30, 2004. Of these inspections, 392,138 resulted in a vehicle placed out-of-service; 135,618 resulted in a driver placed out-of-service; and 28,215 resulted in both the vehicle and the driver placed out-of-service. There are 4,984,278 specific violations associated with these inspections.

Between February 1, 2001 and April 30, 2004, the 540,750 U.S. drivers had 469,321 convictions. These convictions were received by 194,148 unique drivers who had one or more convictions.

- ❑ 2,796 drivers had one or more disqualifying convictions (range of 1 to 6);
- ❑ 100,580 drivers had one or more serious convictions (range of 1 to 18); and
- ❑ 152,025 had one or more other minor convictions (range of 1 to 40).

Table 1 presents a summary of all past crash, violations, and convictions analyzed; their associated crash likelihood increase; and the significance level for the analysis. A significance level of less than 0.05 is considered statistically significant.

The analysis shows that the two *violations* associated with the highest increase in likelihood of a future crash were Reckless Driving and Improper Turns violations. When a driver is cited for one of these violations, their likelihood of a future crash increases 325 percent and 105 percent respectively. Six additional moving violations were significant with an associated crash likelihood increase between 21 percent and 78 percent. Both a log book and a disqualified driver violation were associated with more than a 50 percent increase in the likelihood of a future crash. An hours-of-service violation and a medical certificate violation were associated with a crash likelihood increase of 41 percent and 18 percent, respectively.

The four *convictions* with the highest likelihood of a future crash are:

- ❑ Improper or erratic lane changes;
- ❑ Failure to yield right of way;
- ❑ Improper turn; and,
- ❑ Failure to keep in proper lane convictions.

When a driver is convicted of one of these types of convictions, their likelihood of a future crash increases 91 to 100 percent. Eight additional convictions were significant with an associated crash likelihood increase between 24 percent and 62 percent.

The results of the crash data analysis show that drivers who had a past crash increase their likelihood of a future crash by 87 percent.

Table 1 Summary of Crash Likelihood for all Data Analyzed		
If a driver had:	The crash likelihood increases:	Significance level
A Reckless Driving violation ¹	325%	0.0001
An Improper Turns violation ¹	105%	0.0001
An Improper or Erratic Lane Changes conviction ²	100%	0.0001
A Failure to Yield Right of Way conviction ²	97%	0.0001
An Improper Turn conviction ²	94%	0.0001
A Failure to Keep in Proper Lane conviction ²	91%	0.0001
A Past Crash ³	87%	0.0001
An Improper Lane Change violation ¹	78%	0.0001
A Failure to Yield Right of Way violation ¹	70%	0.0001
A Driving Too Fast for Conditions conviction ²	62%	0.0001
A False or No Log Book violation ¹	56%	0.0001
Any conviction ²	56%	0.0001
A Speeding More Than 15 Miles over Speed Limit conviction ²	56%	0.0001
A Reckless / Careless / Inattentive / Negligent Driving conviction ²	53%	0.0003
A Disqualified Driver violation ¹	51%	0.0001
A Following too closely conviction ²	50%	0.0001
An Improper Lane / Location conviction ²	47%	0.0001
An Hours-of-Service violation ¹	41%	0.0001
Any Moving violation ¹	41%	0.0001
A Following Too Close violation ¹	40%	0.0001
A Speeding violation ¹	35%	0.0001
A Failure to Obey Traffic Control Device violation ¹	30%	0.0001
A Failure to Obey Traffic Signal / Light conviction ²	29%	0.0192
A Speeding 1 to 15 Miles over Speed Limit conviction ²	26%	0.0097
A Failure to Obey Traffic Sign conviction ²	24%	0.0254
A Size and Weight violation ¹	21%	0.0001
A Medical Certificate violation ¹	18%	0.0001
Any OOS violation ¹	16%	0.0001
An Improper Passing violation	25%	0.0684
A Failure to Use / Improper Signal conviction	62%	0.0727
An Improper Pass conviction	50%	0.0748
A Failure to Obey Warning Light / Flasher conviction	109%	0.2676
A Reckless Driving conviction – Serious	21%	0.4857
A Failure to Obey Yield Sign conviction	0%	0.6879

¹Violation

²Conviction

³Separate event

All independent variables from Table 1 was included in the initial model (with a total number of drivers of 245,467), and then a stepwise regression procedure was used to determine the variables that were most significant in the overall model. The final model details are displayed in Table 2. The variables are ordered in Table 2 according to the order the stepwise regression procedure entered them into the model (i.e., the most significant first, given other variables in the model).

Table 2 Overall Model

Variable	Parameter Estimate	Standard Error	Wald Chi-Square	Prob. > Chi-Square	Odds Ratio
Intercept	-3.3017	0.0134	60818.8	0.0001	
False or no log book violation	0.0804	0.0064	157.2	0.0001	1.084
Reckless driving violation	1.3508	0.1651	67.0	0.0001	3.861
Serious speeding conviction	0.1102	0.0207	28.5	0.0001	1.117
A past crash	0.2878	0.0456	39.8	0.0001	1.333
Hours-of-service violation	0.0707	0.0128	30.7	0.0001	1.073
Improper lane change violation	0.3587	0.0738	23.6	0.0001	1.431
Size and weight violation	0.0499	0.0107	21.7	0.0001	1.051
Speeding violation	0.0529	0.0127	17.5	0.0001	1.054
Improper turn violation	0.5119	0.1813	8.0	0.0048	1.668
Failure to keep in proper lane conviction	0.3064	0.1279	5.7	0.0166	1.359
Improper turn conviction	0.4144	0.1713	5.9	0.0156	1.513
Driving too fast for conditions conviction	0.2912	0.1254	5.4	0.0203	1.338
Failure to obey traffic control device violation	0.0969	0.0456	4.5	0.0337	1.102
Failure to yield right of way violation	0.3128	0.1532	4.2	0.0411	1.367

For interpretation of the model, a positive coefficient (parameter estimate) indicates that as the variable *increases*, the driver is more likely to have a future crash. Conversely, a negative coefficient indicates that as the variable *decreases*, the driver is less likely to have a future crash. 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 an example, a driver with a false or no log book violation is estimated to be 1.084 times more likely to have a future crash than a driver without this violation. The other variables are interpreted in the same manner. Examining this particular model, each variable appears to enter the model as would be expected.

Task 2: Relating Data Analysis to Effective Enforcement Countermeasures

According to the state data analysis, the following ten “top tier” states were identified as having more traffic enforcement and lower crashes:

- Washington
- Tennessee
- Iowa
- New Mexico
- California
- Michigan
- Indiana
- Illinois
- Kansas
- Louisiana

Task 3: Identifying Effective Enforcement Countermeasures

The project then identified effective enforcement strategies that were ranked by the top 20 states as strategies that were deemed to be the most successful at addressing problem driver behaviors. The enforcement strategies were identified through the initial basic survey discussed previously.

The findings from the Targeted Survey indicate that successful enforcement strategies for addressing problem driver behaviors are those that exhibit one or more of the following components:

- creating aggressive driving apprehension programs/initiatives;
- focusing on both CMV and non-CMV behavior patterns;
- conducting highly visible enforcement activities;
- using a performance-based approach to identifying specific crash types, driver behaviors and locations; and,
- conducting covert enforcement activities.

Enforcement strategies dealing with speeding and aggressive driving were the most frequently mentioned strategies for targeting problem behaviors. Speed enforcement is generally understood in the enforcement community as dealing with one specific behavior whereas

aggressive driving activities are generally described as a group of problem behaviors including reckless driving, erratic/improper lane changes, following too closely, and improper passing. The National Highway Transportation Safety Administration (NHTSA) defines aggressive driving as, “when individuals commit a combination of moving traffic offenses so as to endanger other persons or property.” (13)

The states of Maryland, New Hampshire, New Jersey, Tennessee, Vermont, and Washington identified specific Aggressive Driver Enforcement Programs that are in use or are being implemented. For example, the Maryland State Police have an aggressive driving initiative entitled Project ADVANCE (Aggressive Driving Video and Non Contact Enforcement) which uses digital imaging and synchronized laser speed detection devices to capture still and video images of vehicles in the act of committing traffic violations. A letter is sent to the owner of the identified vehicle that advises them of the illegal and/or unsafe driving behavior. It was mentioned that this approach is especially useful in highly congested locations where conducting traffic stops is often difficult and unsafe for enforcement officers.

Although this data analysis does not reflect the contributory effects of non-CMV driver behaviors, it is clear from the initial results of the Large Truck Crash Causation study that non-CMV driver behaviors are a major causal factor in crashes where CMV and non-CMV vehicles are involved. For example, Washington State has been selected to design and pilot test a project entitled Ticket Aggressive Cars and Trucks (TACT) that targets collision causing violations around CMVs. The program involves putting a trooper in the cab of a truck and having marked and unmarked patrol cars placed along the freeway in which the trooper calls out violations to the other officers.

It is generally understood in the enforcement community and in previous research that conducting highly visible traffic enforcement is one of the most effective strategies available to deter problem driver behavior as well as a great opportunity to identify and cite such problem driver behaviors as they occur. When drivers perceive that there is a high risk of being caught, their behavior often changes.

The states that were identified as having a higher level of traffic enforcement and a lower level of crashes were found to be significantly more likely to compare traffic enforcement programs with crash data and other information in order to monitor the program’s effectiveness.

Many of the respondents indicated that their agency uses one or more of the following to determine “high risk” locations within their jurisdiction:

- the use of crash data analysis which included crash severity and crash frequencies;
- public complaints; and
- traffic flows and traffic volume.

Using specially marked patrol vehicles that more naturally blend in with regular traffic can provide an excellent opportunity to target both commercial vehicle violators as well as passenger vehicles that inappropriately interact with trucks.

The states that were identified as having a higher level of traffic enforcement and lower crashes levels were found to be significantly more likely to formally develop “best practices” or “lessons learned” from their experiences with traffic enforcement and other enforcement initiatives focused on CMV drivers.

Through interview and survey responses, it appears that having a systematic, multi-faceted enforcement strategy in dealing with problem drivers is more effective. This might be due to several factors:

- ❑ drivers adapt and change behavior quickly to enforcement activities;
- ❑ affecting positive behavioral change in people varies from person to person;
- ❑ the combination of highly visible and unpredictable enforcement strategies keep drivers more honest;
- ❑ it keeps officers fresher since their job responsibilities are flexible and are constantly being adjusted.

RECOMMENDATIONS

To ensure that the research data and findings provide benefit and utility to future CMV safety objectives and research efforts, the research team has identified a series of “next steps” for consideration:

- ❑ Based on the results of the data analysis, enforcement agencies may want to focus attention on singular problem behaviors rather than large groupings in order to have the most profound impact on reducing CMV-involved crashes.
- ❑ States should develop and adhere to comprehensive self-assessment and data monitoring programs. These types of programs provide immediate feedback on performance, and allow agencies to be more flexible and strategic in their approaches.
- ❑ Create a more formal process for documenting and disseminating best practices for enforcement strategies on problem driver behaviors.
- ❑ Communicate the data and results of this research to CMV and non-CMV enforcement agencies.
- ❑ Sworn law enforcement officers and CMV (civilian) inspectors should have the necessary authority to address CMV and non-CMV problem driver behaviors.
- ❑ Develop standardized training for CMV and non-CMV enforcement officers that helps to facilitate effective and uniform enforcement of problem driver behaviors by CMV and non-CMV (in the vicinity of CMVs) operators.
- ❑ A system is needed to uniformly and effectively capture data on problem behaviors exhibited by non-CMV drivers around CMV drivers.
- ❑ Direct more resources to enforcement strategies targeted at problem driver behaviors and traffic enforcement activities.
- ❑ Create a monitoring program with which to effectively and uniformly measure enforcement inputs and outputs to help in the allocation and deployment of resources.
- ❑ Study the effectiveness and costs-benefits of the various aggressive driver programs.
- ❑ Enforcement agencies need to have an appropriate level of resources dedicated (internal or external) to data acquisition and analysis to facilitate performance-based strategies.
- ❑ Pursue the development of targeted communication initiatives to supplement enforcement activities.

- ❑ Enhance and streamline enforcement officers' ability to identify and address drivers exhibiting these types of behaviors.
- ❑ Develop a federal funding program for field operational tests of promising technology solutions for enforcement.
- ❑ Engage political, regulatory, enforcement, licensing and judicial organizations in a dialogue outlining these problem behaviors and identify solutions for minimizing their occurrence in the future. This should be done on local, regional and national levels.

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