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Driver Fatigue Enforcement Techniques and Their Effect on Crashes

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DRIVER FATIGUE ENFORCEMENT TECHNIQUES AND THEIR EFFECT ON CRASHES

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DRIVER FATIGUE ENFORCEMENT TECHNIQUES AND THEIR EFFECT ON CRASHES

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Fatigued driving is a type of driver impairment caused by a lack of sleep, sleep disorders, long drive times, etc. Fatigued driving enforcement aims to improve safety by removing impaired drivers from the roadway. While fatigued driving is detrimental to safety, there exists the issue of identifying fatigue. There is a range between being awake and asleep and, in order to improve safety, enforcement officers must be able to identify the point at which drivers are impaired.

This thesis investigates potentially effective fatigued driving enforcement techniques for use by enforcement officers. These techniques were investigated through three primary means: a literature review, a nationwide telephone survey, and a statistical estimation of crash models. The telephone survey was administered to state patrol agencies across the United States. It collected information related to fatigued driving policies and procedures. The collected data were coded into a spreadsheet and analyzed using statistical models of fatigue-involved crashes.

Three fatigue-involved crash models were estimated with data from the telephone survey and crash databases. Two crash frequency models were estimated. Both were negative binomial models and used the sum of fatigue-involved crashes over a certain time period as the dependent variable. The first crash frequency model only considered

fatigue-involved fatal crashes while the second considered all fatigue-involved crashes. A crash severity model was estimated as well.

The crash models provided evidence that certain fatigued driving enforcement techniques had a positive impact on roadway safety. States with fatigued driving related law enforcement training and driver education programs tended to be safer than those that did not have such programs. The technique shown to have the greatest impact on fatigue related safety was the use of driving cues to determine if a driver was fatigued. This was the only technique significant in two crash models. The use of driving cues to identify fatigued driving appears to be an effective method for improving safety. Further research is necessary to better understand the issue of fatigued driving and to objectively identify fatigue.

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1.0 INTRODUCTION

Driver fatigue has been recognized as a detriment to roadway safety (Sagberg & Bjornskau, 2007). In the case of commercial motor vehicle (CMV) drivers, fatigue is a natural concern as the profession involves long driving hours. Current regulations for commercial drivers focus on limiting driver workload and requiring rest breaks through the Federal Hours of Service (HOS) regulations. Outside of these regulations, it is a driver's prerogative to rest when he or she feels it is necessary. It is possible that commercial drivers will not rest as often as they should and operate his or her vehicle while fatigued.

The federal government considers fatigue to be a major safety concern in the case of commercial drivers. The Federal Motor Carrier Safety Administration (FMCSA) regulation §392.2 addresses this issue. The following is an excerpt from this regulation:

> No driver shall operate a commercial motor vehicle, and a motor carrier shall not require or permit a driver to operate a commercial motor vehicle, while the driver's ability or alertness is so impaired, or so likely to become impaired, through fatigue, illness, or any other cause, as to make it unsafe for him/her to begin or continue to operate the commercial motor vehicle.

While fatigue is recognized to be an issue for commercial drivers, there is little guidance, if any, available on fatigue recognition. The Nebraska State Patrol (NSP) is interested in determining signs of driver fatigue which law enforcement officers may potentially use to identify commercial drivers who are driving while fatigued and subsequently remove them from the roadway. The Nebraska Department of Roads

(NDOR) is interested in determining characteristics of fatigue-involved crashes and exploring countermeasures to mitigate the occurrence and severity of such crashes.

This research focused on investigating methods of fatigue determination which may be utilized by the Nebraska State Patrol or other law enforcement agencies for fatigued driving enforcement of commercial drivers. If practical and effective methods were found, they could be implemented in the case of non-commercial drivers as well. As part of this research, a survey of state patrol agencies across the United States was administered to identify policies and procedures currently in place related to fatigued driving. The survey data was used in conjunction with multi-year fatigue-involved fatal crash data to determine their safety effects. Fatigue-involved fatal crash data were obtained from the US Department of Transportation's (USDOT) Fatal Accident Reporting System. To investigate the role of fatigue on crash injury severity, data from the USDOT's Highway Safety Information System (HSIS) was utilized. A literature review of published research related to fatigue identification was performed. Based upon the results, future analysis of fatigue determination techniques deemed promising could be performed.

This thesis presents a problem statement describing the specific issues investigated in this research. The sections following the problems statement present the research objectives, study outline, data collection, data analysis, results, model limitations, and final conclusions. A literature review is included which presents information from published literature related to the safety effects of fatigued driving, fatigue categorization and identification techniques, and causes of fatigue.

The data collection section describes the creation of a telephone survey and its administration to state patrol agencies, as well as information regarding databases used to retrieve fatigue-involved crash data. The data analysis section details the process used to reduce the data, estimate statistical models, and the reasons specific models were chosen. A results section provides the final estimated statistical models and descriptive statistics related to the crash data. Following the results, a section is included which describes limitations of the crash models. A conclusions section presents information gleaned from the statistical models, telephone survey, and literature review related to potentially effective fatigued driving enforcement techniques. Recommendations about these techniques are presented. The conclusions section includes information related to any potential challenges associated with enforcement techniques suggested from the telephone survey.

1.1 Problem Statement

It is well established that fatigued driving negatively affects highway safety (Feyer & Williamson, 2001). As the subsequent literature review shows, there is no widely accepted method for determining drivers' fatigue levels as various enforcement techniques are in use by different state patrol agencies. While identification techniques have been studied, relatively little research was uncovered in terms of how fatigued driving enforcement affects safety. The primary goal of enforcement is to improve safety for all users, so this investigation is necessary for a better understanding of the issue of fatigued driving. Additionally, roadway and traffic characteristics associated with fatigue-involved crash injury severity need investigation for a more in-depth understanding to allow transportation agencies to better mitigate the severity of such crashes.

1.2 Research Objectives

This research aims to collect data on fatigued driving policies and practices of different state patrol agencies across the US through the use of a telephone survey. Survey results were related to reported fatigue-involved fatal crashes to identify fatigued driving enforcement techniques which are positively affecting safety on roadways. Additionally, this research identified roadway and traffic characteristics associated with injury severity of fatigue-involved crashes. Crash frequency and crash severity models were estimated to objectively determine the effects of enforcement techniques. A literature review, the telephone survey results, and the crash models provide information related to potentially effective fatigued driving enforcement techniques for use by law enforcement officers.

1.3 Research Program

The study was performed through four primary tasks. Each task is described in detail later in this report. The following sections give a brief overview of each task.

1.3.1 Task 1: Literature Review

A literature review was performed to identify causes of fatigue, categorization and identification techniques related to fatigue, and the effects of fatigued driving on roadway safety. Specifically related to safety, the issue of fatigue amongst drivers and injury severity of fatigue-involved crashes was reviewed in published research. This review is included in a later section of this report. Articles related to fatigue identification were retrieved from the Transportation Research Record (TRR) and the Transportation Research Information Service (TRIS). Additional information related to statistical modeling techniques was retrieved to ensure the models used to analyze the survey results were appropriate.

1.3.2 Task 2: Data Collection

A telephone survey seeking data on state patrol agency policies and practices dealing with commercial motor vehicle driver fatigue was designed at the University of Nebraska-Lincoln (UNL). The survey was administered with the help of the UNL Bureau of Sociological Research (BOSR). BOSR specializes in survey research and ensured the survey was administered professionally and in a timely manner. The survey results were charted in a spreadsheet and combined with crash data obtained from the FARS and HSIS databases.

1.3.3 Task 3: Data Analysis

Statistical models were estimated to analyze the data retrieved through the telephone survey and crash databases. These models investigated associations among states' policies and procedures related to fatigue and the number of fatigue-involved fatal crashes and the severity of fatigue-involved crashes. Descriptive statistics were performed on the FARS data to gain a better understanding of how fatigued driving is approached in different states.

1.3.4 Task 4: Conclusions and Recommendations

Conclusions from the statistical models were made. The statistical models had various shortcomings related to the involved data. These limitations are discussed later in the report. The model results, in conjunction with information from the telephone survey and literature review, led to recommendations about potentially effective fatigued driving enforcement techniques. Further recommendations were made regarding future research related to fatigued driving enforcement.

2.0 LITERATURE REVIEW

Driver fatigue is a major concern, especially for commercial drivers. Fatigue is difficult to evaluate as there is a continuing scale from being awake to being asleep and fatigue comprises the levels in between. Fatigue may have physical or psychological causes, ranging from sleep problems to the road environment. Previously, countermeasures for commercial driver fatigue have focused on driver workload. Research indicates the time of day of driving may have a greater impact on fatigue than workload (Sagberg & Bjornskau, 2007). Many technologies have been introduced to detect driver fatigue. The majority of these utilize physiological symptoms, particularly eye closure, heart rate, or respiratory patterns. Others rely solely upon steering cues. Law enforcement may be able to use a combination of steering and physiological cues to detect driver fatigue.

2.1 Fatigued Driving Safety Effects

Driving while fatigued is a common problem among drivers and causes severe safety problems. Fatigued driving is responsible for numerous crashes and fatalities each year (Eskandarian, 2010). Sagberg and Bjornskau (2007) surveyed 4448 crash-involved drivers in Norway. Of those questioned, six percent admitted to falling asleep at the wheel in the past year, and 22 percent reported they had fallen asleep at the wheel while driving at some point. Fatigue is a particular issue in the case of commercial drivers as they must drive long shifts in specific time frames. It is estimated 40-50 percent of fatal single vehicle semitrailer crashes in Australia are caused by fatigue (Feyer & Williamson, 2001). This problem is prevalent in the United States as well. Morrow and Crum (2004) surveyed 116 trucking firms in the United States to determine how driver fatigue affects crashes and near-crashes for commercial drivers. They concluded fatigued driving greatly increased the number of crashes and near-crashes for commercial drivers.

Fatigue negatively impacts safety by increasing the likelihood of a crash, but more research needs to be performed to determine how fatigue affects crash severity (Kaplan & Prato, 2012). The majority of existing research considers fatigue to be positively associated with crash severity. Eskandarian (2010) found drivers in fatigue-related crashes to be less likely to respond to hazards. A loss of driver control and no braking response leads to more severe crashes. Kaplan and Prato (2012) created a mixed logit model to investigate the likelihood a crash avoidance maneuver. Fatigue was found to have a greater negative correlation with avoidance maneuvers than with impairments from drugs and alcohol. Fatigue may be similarly risky to driving while under the influence of drugs or alcohol. The lack of avoidance techniques may lead to more severe crashes.

Anund, Kecklund, and Aakerstedt (2011) created a logistic model to investigate the effect of fatigue on crash severity. Most fatigue-related crashes are single-vehicle, run-off-the-road crashes. Fatigue was seen to increase the severity of this type of crash. Similarly, Soufiane and Williamson (2009) performed multivariate analyses to determine factors which contribute to crash severity. Fatigue was seen to be positively associated with crash severity. A study in Finland by Radun, Radun, and Ohisalo (2009) also found most fatigue-involved crashes to include a single vehicle. Of those, 81.6 percent did not result in an injury.

2.2 Fatigue Categorization

While the dangers of fatigued driving are well understood, there is currently no accepted method to evaluate and quantify a driver’s drowsiness level (Wierwille & Ellsworth, 1994). The lack of an objective way of determining fatigue may mean fatigued driving is underreported. Studies have estimated one to four percent of crashes to be caused by fatigue. Actual crash records often attribute two to three percent of crashes to fatigue (National Highway Traffic Safety Administration, 1994). Haworth (1998) found fatigue to be more prevalent in commercial motor vehicle crashes. In Australia, five to ten percent of commercial motor vehicle crashes have been attributed to fatigue. Until enforcement officers are able to accurately recognize and quantify fatigue, fatigue-involved crashes may not be reported with any certainty.

Multiple measures have been suggested to quantify fatigue. All methods recognize a range of fatigue levels which may be difficult to distinguish and difficult to implement for non-research use. Wierwille and Ellsworth (1994) utilized an observer rating. In their study, trained observers evaluated driver drowsiness from video recordings of the drivers' faces. The trained observers gave repeatable results, but other studies or non-research settings may not have sufficient resources to use this rating system.

Specific levels of fatigue were used in a study of 21 middle aged men and ten male college students. Participants were asked to report their own sleepiness on a scale of one to four (1: awake, 2: slightly sleepy, 3: very sleepy, 4: almost asleep) (Miyake et al., 2010). Having participants rate themselves introduces the possibility of different perceptions of the definition of "very" versus "slightly" sleepy. In an attempt to avoid subjectivity or personal bias, the International Association for Accident and Traffic Medicine delineates fatigue into four categories based upon a person's ability to do mental calculations (1983). Mental calculations describe a person's concentration level and may be effective in determining fatigue if each level is well-defined. This approach is more easily implemented in law enforcement situations as little training would be necessary to utilize a comparable system.

2.3 Causes of Fatigue

Driver fatigue may have many causes which can be considered either physical or psychological in nature (International Association for Accident and Traffic Medicine, 1983). Physical fatigue is most often caused by a lack of sleep. A Norwegian study found that drivers reported some kind of sleep problem in approximately 40 percent of crashes involving fatigued driving (Sagberg, 2008). Psychological fatigue may have many causes. A study of fifty participants in a driving simulator determined potential causes of psychological fatigue. Outcome measures included sleepiness, low healthy lifestyle status, an extroverted personality, and negative mood states (Wijesuriya, Tran, & Craig, 2007). Nakayama (2002) found the primary cause of psychological fatigue to be long driving workloads in a study of 20 volunteers.

Limiting workload is the primary control currently used to discourage fatigued driving by commercial drivers by means of Federal Hours of Service (HOS) regulations. There is significant evidence suggesting driver workload has a critical influence on driver fatigue. A study of volunteers found a dramatic increase of fatigue after 12 hours of driving time (Nakayama, 2002). Similar results are seen in the case of commercial drivers. Jovanis, Wu, and Chen (2011) analyzed carrier-supplied driver logs to determine the probability of a crash after a certain amount of driving time. It was found there is a consistent increase in crash odds with increased driving time. This increase is particularly evident after six hours of driving. These crash odds decreased if breaks were taken. A second break reduced crash odds by 32 percent for those driving truckload vehicles, and 51 percent for those driving less than truck load vehicles.

While federal regulations focus on workload limitations to counteract fatigue, more than just the length of drive time can have an effect. Oron-Gilad and Hancock (2005) consider there to be two main causes of fatigue: the driver’s state before the drive begins and the characteristics of the drive and road environment. Possible drive characteristics and road environment factors were investigated by a questionnaire which was distributed to drivers in Norway. Sagberg and Bjornskau (2007) found drivers more often fell asleep in situations with little traffic, high speed limits, straight roadways, and good weather. These drive characteristics are particularly common for commercial drivers.

Feyer and Williamson (2001) suggest that night work, timing of work periods in succession, and time off between periods of work are also important influences on long-distance driver fatigue. These factors had been previously investigated by Wiley et al. (1996). Eighty commercial drivers in the United States and Canada were monitored for 16 weeks. Driver fatigue was measured with video recordings of the drivers' faces. Driver workload, consecutive driving days, time of day, and schedule regularity were all considered as potential influences for fatigue. The most consistent influence on fatigue was found to be the time of day when driving took place.

Similar results were found by a study of 900 hours of naturalistic driving. The study aimed to determine operational or driving environment influences on fatigue. Again, time of day of the driving shift had the greatest impact on a drivers' potential to become fatigued. The study found a driver was twice as likely to become drowsy between 6:00 and 9:00 am. Thirty percent of all drowsiness incidents occurred during the first hour of the work shift (Barr et al., 2005). These conclusions were reiterated by the results of a questionnaire distributed in Norway. The risk of falling asleep is 17 times higher between midnight and 6:00 am, than 6:00 am and noon (Sagberg & Bjornskau, 2007).

2.4 Fatigue Identification

Even if the causes of fatigue are known, there still exists the problem of being able to recognize fatigue. Several technologies have been introduced to detect driver fatigue, the majority relying on visual cues of the drivers. Some of these technologies aim to alert the driver of a possible unsafe situation. Kaneda et al. (1995) created a detection method to measure driver drowsiness. A video camera captures images of the driver's face and detects limited alertness by measuring how far open a driver's eyes are. If the system considers a driver to be fatigued, the device emits an audible warning followed by a menthol scent to help wake the driver. It was found that a menthol scent in addition to an audible warning is more than twice as effective as the audible warning alone.

Eye closure is commonly used in driver fatigue detectors. A study was performed at the University of Iowa which used video recording to follow a subject's face. Algorithms were used which automatically located a driver's eyes. Visible eye features were monitored; an alarm sounded if the eyes were closed for longer than 1.5 seconds. This process also monitored the area of exposed eye features and an alarm sounded if there was a sustained reduction in this area (eyelid droop) (Bishop & Evans, 2001). Singh and Papanikolopoulos (1999) recommend a similar system which focused on drivers' eyes. They presented a system which tracked a driver's pupil and monitored the eyes for micro-sleeps by counting video frames when the eyes were closed. Lal and Craig (2000) found drowsiness to be easily recognized by a subject's fast, rhythmic blinking and little eye movement.

Visual cues from a driver's face may be utilized by law enforcement to detect driver fatigue. Blinking patterns and eyelid droop can be easily seen during a traffic stop, but may not be sufficient to detect driver fatigue. A traffic stop may be sufficiently stressful to temporarily raise alertness in the driver and lessen these symptoms. Also, individuals vary in their natural blinking patterns and an officer does not have a good base line with which to compare those patterns. Further study would be necessary to determine if these techniques could be used by law enforcement officers.

While eye closure may be an effective method to determine driver fatigue, other symptoms may be used as well. De Rosario et al. (2010) investigated biomedical and biomechanical signals which may be able to detect driver drowsiness. These factors specifically included biomedical signals, eye closure, pressures on the seat, and control of the vehicle. Electroencephalography (EEG) readings and the percent of eye closure were used as the primary indicators of drowsiness to compare to the other factors. This study found heart rate variability and respiration to be the most promising indicators of drowsiness. Lal and Craig (2000) also found heart rate to be a good indicator of fatigue. As subjects performed in a driver simulator, a reduced heart rate was seen in all participants as they fatigued.

Heart rate has been used in multiple studies as an indicator of fatigue. In a study of volunteers, a high correlation between pulse rate and fatigue was found (Nakayama, 2002). For this reason, Nakano et al. (2008) introduced a drowsiness detector which relies on a measure of the driver's heart rate taken through a sensor on the steering wheel. Heart rate may be used in addition to other physiological symptoms. Heart rate, skin conduction, electromyogram, skin temperature, and respiration measures were used in eight simulations; 93.75 percent of normal and abnormal states and 63.64 percent of transitional and fatigue levels were correctly identified (Mao, Yan, & Wu, 2008).

Respiration may be used as an indicator of fatigue by law enforcement. Heart rate is not as effective of an indicator as it is not as visually recognizable as breathing patterns. In both cases, problems may arise as a traffic stop may be stressful on the driver and temporarily raise the driver's heart rate and increase their respiration, masking the fatigue symptoms.

While physiological symptoms are commonly used to diagnose fatigue, many other detection methods take a different approach. A fatigue monitoring system has been created which relies solely on steering behavior. Patterns of slow drifting and fast corrective counter steering are expected in fatigued driving. When used in a driving simulator in a sleep deprivation study of 12 participants, an 86.1% recognition rate was seen in classifying slight from strong fatigue (Krajewski et al., 2009). Mortazavi, Eskandarian, and Sayed (2009) also found steering behaviors to be sufficient indicators of drowsiness. In a driving simulator with commercial driver subjects, lateral position variations and steering corrections were observed. Significant patterns were observed and deemed sufficient to identify driver drowsiness. Steering patterns may be a good indicator to be utilized by law enforcement. Lane position variation and quick, corrective steering movements may be easily observed.

Though steering patterns or physiological symptoms may indicate fatigue, Kircher, Uddman, and Sandin (2002) suggest there is no sufficiently reliable commercial system available for detecting driver drowsiness. No single indicator is sufficient to indicate drowsy driving. Instead, they suggest a combination of eye blink pattern and lateral control performance for detection of drowsiness. Similarly, steering and physiological cues may be used in conjunction by law enforcement to better detect driver fatigue.

Several types of potential fatigue identification techniques have been introduced in the previous section. These techniques are summarized in Figure 1.

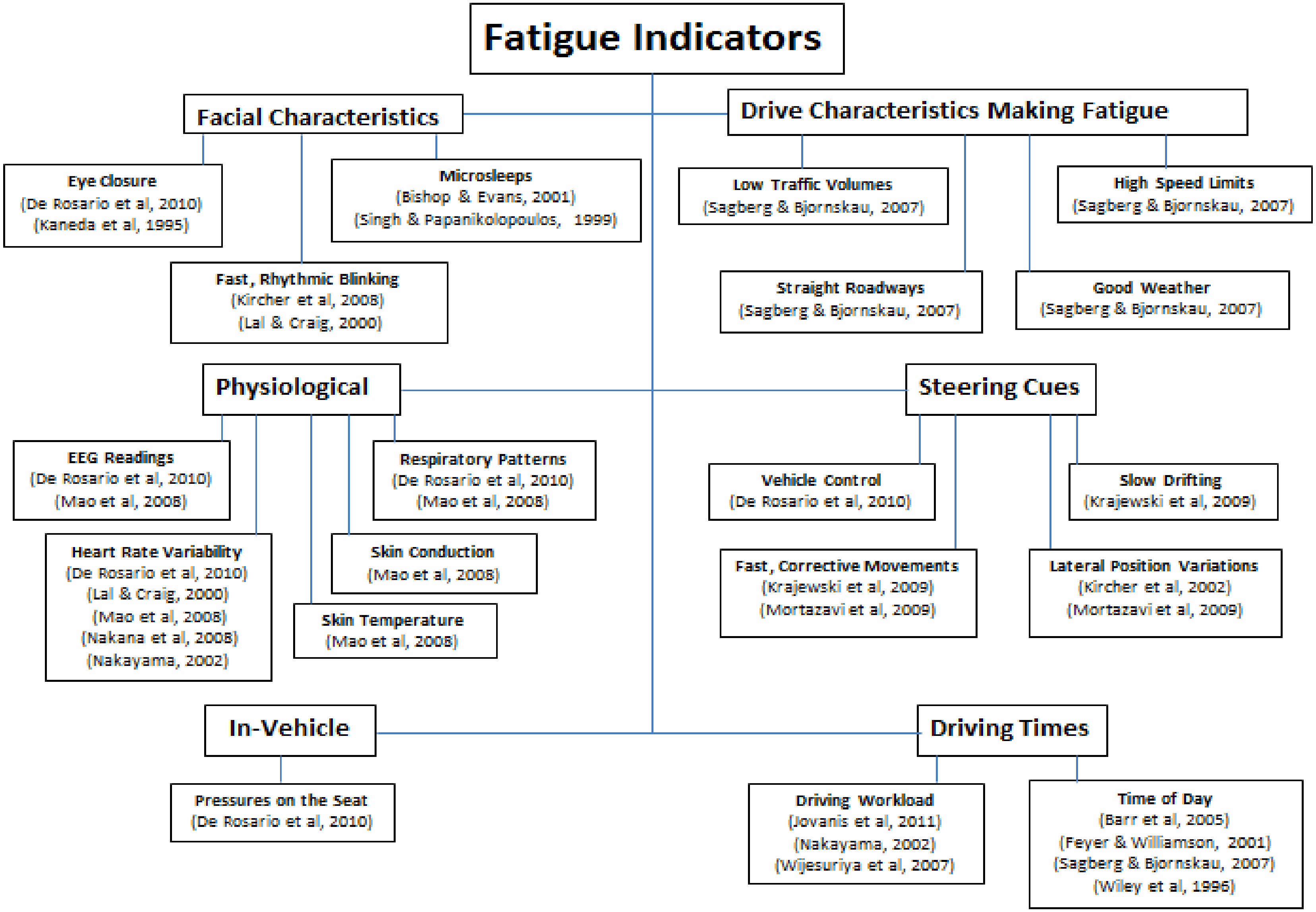

Figure 1. Fatigue identification techniques

Previous research has shown that many drivers are aware they are becoming fatigued. A questionnaire of drivers in Norway found that most drivers who fell asleep at the wheel reported feeling tired beforehand and attempted to stay awake by implementing practices such as playing music, opening a window, or putting on the fan (Sagberg & Bjornskau, 2007). Gershon et al. (2011) distributed a survey to 100 professional and 90 non-professional drivers to evaluate the perceived effectiveness of fatigue coping mechanisms. Both professionals and non-professionals considered listening to the radio and opening the window as the most effective approaches. Commercial drivers also considered planning ahead for rest stops, stopping for short naps, and drinking coffee to be effective fatigue coping measures (Gershon et al., 2011). Imberger, Styles, and Walsh (2009) found playing music and rolling down a window to be ineffective methods to increase alertness. Naps and caffeine may be effective countermeasures.

2.5 Fatigued Driving Regulations

The Federal Motor Carrier Safety Administration (FMCSA) regulations consider fatigue to be a safety concern in the case of commercial vehicle drivers. The following is an excerpt of FMCSA regulation §392.2 addressing the issue of fatigued driving:

> No driver shall operate a commercial motor vehicle, and a motor carrier shall not require or permit a driver to operate a commercial motor vehicle, while the driver's ability or alertness is so impaired, or so likely to become impaired, through fatigue, illness, or any other cause, as to make it unsafe for him/her to begin or continue to operate the commercial motor vehicle.

In accordance with this regulation, a commercial vehicle inspection may include checking the driver for signs of fatigue. The United States Department of Transportation created procedures for different levels of inspection to be utilized by the states. A Level 1 Truck Safety Inspection includes a step of approaching the driver. Within this step, the inspector will, “observe the driver’s overall condition for illness, fatigue or other signs of impairment” (U.S. Department of Transportation). No guidance is given for distinguishing fatigue.

States have the ability to determine the specific procedures for vehicle inspections beyond those stipulated by the federal government. These procedures mimic the Level 1 Inspection previously described. Fatigue is often mentioned in these procedures, but policies are not well defined. The state of Ohio’s Commercial Motor Vehicle Inspection Process has inspectors check, “the condition of the driver for signs of fatigue” (Public Utilities Commission). Once again, no specifics are given on the signs of fatigue.

Driver fatigue has long been considered a safety concern. Though it is difficult to quantify, fatigue is understood to be a range which may be caused by physical or psychological conditions. The primary measure used to counteract commercial driver fatigue has been a limit on a driver’s workload. There is evidence to show that while workload is a factor in fatigue, the time of day of driving has a bigger impact. Numerous methods have been used to detect driver fatigue, the majority relying on visual cues such as percent of eye closure and blinking patterns. Heart rate, respiratory patterns, and steering variations have also shown promise as indicators of fatigue. Both physiological and steering cues may be used by law enforcement to more successfully detect situations of driver fatigue.

2.6 Crash Modeling Techniques

This research used statistical models to analyze the effectiveness of fatigued driving enforcement techniques on crash frequency and injury severity of fatigue-involved crashes. The literature review included investigation into which models and statistical distributions have been used to model fatigue-involved crashes to ensure that proper models were utilized for data analysis.

2.6.1 Crash Frequency Modeling Techniques

Many types of models have been used in the past to model crash frequency. These include linear regression, Poisson, and negative binomial models. The linear regression model is no longer commonly used because it allows the prediction of negative values. This is obviously inappropriate for crashes which cannot take negative values (Carson & Mannering, 2000).

Recently, negative binomial models and zero-inflated Poisson models have become more popular for crash analysis. A Poisson regression model takes the form (Carson & Mannering, 2000):

$$P(Y_i) = \frac{e^{(-\lambda_t)}\left(\lambda_t^{Y_t}\right)}{Y_t!}$$

Where $P(Y_t)$ is the probability of Y_t crashes at a location, i, over a specified time period. The value, λ_t, is the Poisson parameter equal to the expected value of $Y_t(E[Y_t])$. Next, covariates are introduced into the model with:

$$\lambda_t = \exp\,(\beta X_t)$$

The vector of estimable coefficients is represented by β while X_t is the vector of covariates. Standard maximum likelihood methods are used to estimate the value of β.

This often leads to an issue of overdispersion (Carson & Mannering, 2000). That is, the Poisson model assumes the mean and variance of the dependent variable (Y_t) to be equal. Overdispersion, variance significantly greater than the mean, is common in crash data. A negative binomial model can be appropriate in the case of overdispersion because it relaxes the constraint of equal variance and mean.

Issues can arise in Poisson and negative binomial models if too many data points are equal to zero. Crashes are rare occurrences so a dataset may contain excess zeros. A value of zero in a model may be a true or false zero. A true zero represents a time period when a certain situation, in this case a crash, could have occurred but did not. There is also the possibility of a false zero where no event is observed due to sampling errors. If excess zeros do exist in the data set, zero-inflated Poisson or zero-inflated negative binomial models may be appropriate. The Vuong's test is used to determine the appropriateness of a zero-inflated model. The Vuong test is comprised of a t-statistic test done with the following equation (Carson & Mannering, 2000):

$$V = \frac{\overline{m}\sqrt{N}}{S_m}$$

Where $\overline{m}$ is the mean of $m=\log[f_1(.)/f_2(.2)$. The function, $f_1(.)$, is the density function of the zero-inflated negative binomial distribution. The function, $f_2(.)$, is the density function of a traditional negative binomial distribution. S_m and N are the standard deviation of m and the sample size, respectively. A value of V greater than 1.96 implies a zero-inflated negative binomial model is appropriate, while a value of V smaller than -1.96 implies a traditional negative binomial model is appropriate. A value of V between -1.96 and 1.96 indicates an inconclusive test. The previous section described the test for the appropriateness of a zero-inflated negative binomial model. The same procedure is used when testing the appropriateness of a zero-inflated Poisson model (Carson & Mannering, 2000).

2.6.2 Crash Severity Modeling Techniques

Crash severity is an inherently continuous variable but is recorded on an ordinal scale. Police crash reports record crash severity as being of a specific group. Severity is grouped into categories, but these categories do not capture variation within each severity level. Models rely on fixed parameters to estimate severity with limited, often biased information from crash reports and a small sample size (Mannering, Lord, and Quddus, 2011).

Carson and Mannering (2000) suggest a crash severity model should be specific to a roadway class. For example, create a model for all crashes on interstate highways, another for crashes reported on principle arterials, etc. Eluru et al. (2012) also stressed the importance of correctly correlating crashes with roadway characteristics. They do not consider separate models necessary, but recommend segmenting the roadway based on characteristics. This can introduce some ambiguity into the model as it is difficult to know the best way to separate the roadway into segments.

Different models have been suggested based on the way analysts choose to categorize crash severity. Eluru, Bhat, and Hensher (2007) recommend a logistic regression model when severity is categorized in binary form. A common binary form of crash severity is recording a crash as either fatal or non-fatal. Binary logit or binary probit models are used in this case (Mannering, Lord, & Quddus, 2011).

The KABCO scale is a common way to categorize injury severity. An enforcement officer classifies the injury severity of a crash as one of five categories: K – killed, A – disabling injury, B – evident injury, C – possible injury (complaint of pain, and O – property damage only (no injury). If the full KABCO scale is used, an ordered response model (generally an ordered probit or ordered logit) is appropriate (Eluru, Bhat, & Hensher, 2007). These models are most commonly used for ordinal crash severity data. This type of model suffers from underreporting bias which is difficult to correct (Mannering, Lord, & Quddus, 2011).

In an ordered response logit model, q (q=1,2, . . . , Q) is an index which represents individuals involved in the crash. Injury severity is represented by k, which may follow the KABCO scale. In this case, k takes values between one and five, with one representing property damage only crashes and five representing fatal crashes. The ordered response logit model takes the form (Mannering, Lord, & Quddus, 2011):

$$y_q^* = \beta' x_q + \varepsilon_q, \quad y_q = k \text{ if } \psi_{k-1} < y_q^* < \psi_k$$

Where y_q^* represents the latent injury risk for an individual, q, in a crash. The variables, x_q and β', represent attributes of the roadway, surrounding environment, driver, crash, etc. The variable, ψ, is a threshold which separates the levels of severity. There are k-1 thresholds as the outer most severity levels extend to -∞ and ∞. Random error in the model is represented by ε_q. The ordered response logit model allows for non-linear effects of any variable (Mannering, Lord, & Quddus, 2011). An ordered probit model is very similar to an ordered logit model. They differ in the assumption of the distribution of the error terms. The probit model assumes error terms to be normally distributed while the logit model assumes the error terms to be logistically distributed (Savolainen et al., 2011).

Ordered models are the traditional choice when modeling crash severity but have certain limitations. The primary limitation of ordered models is that the thresholds are held constant across all crashes (Eluru, Bhat, & Hensher, 2007). Also, ordered probit and ordered logit models are biased when considering the injury severity of more than one individual involved in the crash. These models are not capable of capturing multiple injury severities. Only the most severe injury is recorded with the KABCO scale. The other individuals involved in the crash are ignored. Bivariate probit models may be used to model the injury severity of multiple individuals. Some assumptions in ordered response models may not be entirely true. An ordered model assumes equal error variances which are often not true (Savolainen et al., 2011).

Ordered response models hold the threshold values constant over all cases. This may not be the best way to model the data as variable thresholds provide more opportunities for model calibration. A generalized logit model allows these thresholds to vary. The mixed generalized logit model takes a similar form to that of the ordered logit model but introduces other parameters which allow for the threshold variation (Eluru, Bhat, & Hensher, 2007).

Several extensions of the traditional ordered models exist. One such model is a bivariate ordered probit model which uses a hierarchical system of two equations. Both equations work simultaneously to model the situation (Mannering, Lord, & Quddus, 2011). Bayesian and mixed/random parameter logit and probit models are similar to traditional ordered models but may improve the models by accounting for unobserved effects. Independent variables only provide a partial understanding of the model and some effects are not captured. Unobserved effects cause some error in the model. If three or more outcomes are being considered which are not discrete, a multinomial logit model is used. A nested logit model is a generalization of the multinomial logit model. (Savolainen et al., 2011).

Even if an appropriate distribution is chosen to model a specific crash severity situation, it is important to include relevant variables in the analysis. Chen and Jovanis (2000) suggest log-linear modeling techniques can improve logit models by analyzing interactions among different variables. Chi-squared tests are used to understand associations between variables. Variables which are highly associated with each other are not independent. If an association is seen, one variable is removed from the analysis.

There are many potential distributions to be considered when modeling crash severity. Abdel-Aty (2003) compared the results of different injury severity models including multinomial logit, nested logit, and ordered logit and probit models. Results from ordered probit and logit models were shown to be very similar. Nested logit models were shown as an improvement over traditional ordered models when the data were separated into groups, such as truck and non-truck crashes. Multinomial logit models gave inferior results when compared to the results obtained from ordered models. While the nested logit models gave the best results, ordered logit and probit models were much easier to estimate and are often a good choice for a preliminary investigation.

Ye and Lord (2013) compared the results of ordered probit, mixed logit, and multinomial logit models used for crash severity analysis. Sample size appeared to have a significant impact on the effectiveness of a model and none of the models performed well with sample sizes less than 500 observations. Ordered probit models required the smallest sample size for stability of around 1,000 data points. Multinomial logit models required sample sizes greater than 2,000 data points, while mixed logit models required 5,000 data points. Of the three models tested, the ordered probit model retained the most variables as statistically significant. Ordered models appeared to perform the best when there were limited data available.

3.0 DATA COLLECTION

The primary method for investigating fatigue identification techniques in use by law enforcement officials was a telephone survey of agencies across the US. A telephone survey was created and is shown in Appendix A. State patrol agencies from 49 states were surveyed (Hawaii does not have a state patrol agency). Contact information for each agency was retrieved from its respective website. The telephone survey was administered by the University of Nebraska-Lincoln Bureau of Sociological Research (BOSR). BOSR specializes in survey research; their participation ensured the survey was administered in a timely and professional manner. As contact information was found online, the person first contacted was often not the person best suited to answer the questions. If necessary, the surveyor was referred to another person who could better respond to the survey. All state patrol agencies were contacted and surveyed successfully though some respondents did not know the answers to specific questions.

Additionally, crash data were retrieved to complement the survey data. Data resources included the Fatal Accident Reporting System (FARS) database and the Highway Safety Information System (HSIS) database. Both crash databases provide a crash cause and include fatigue as a potential cause. Only data pertaining to fatigue-involved crashes was retrieved. Information was retrieved from other sources to provide more variables to be used in the statistical models. Specifically, vehicle miles traveled information was retrieved from the Federal Highway Administration (FHWA) website. Information regarding commercial motor vehicle inspections and state specific out-of-service percentages were retrieved from the Federal Motor Carrier Safety Administration online Summary of Roadside Inspections. Data from the disparate sources were combined for subsequent analysis, which is described next.

4.0 DATA ANALYSIS

The data retrieved from the telephone survey and other sources was analyzed to gain an understanding of fatigue-involved crashes. The following sections describe how each data source was analyzed.

4.1 Survey Data Analysis

After the telephone survey was administered, it became obvious there was some ambiguity in the survey questions. Respondents interpreted Question 5 differently, which stated, “Does your agency have published rules and regulations dealing with the issue of fatigue in commercial motor vehicle drivers?” This question requested a “yes” or “no” response, but many respondents included qualitative information in addition to a “yes” or “no” response. Of the total respondents, 46 mentioned federal regulations in response to Question 5 but some respondents considered federal regulations to qualify as a “yes” response, while others considered it a “no” as they did not have any state-specific regulations in addition to the federally mandated ones. In such cases, responses were altered based upon respondent explanations to avoid bias.

Several telephone survey questions requested qualitative information. Indicator variables were created for common answers to such questions to allow for usage in the statistical models. For example, Question 9 states, “What procedure is followed when an officer stops a driver believed to be fatigued?” Eighteen respondents stated that officers perform an interview of the driver in this case. An indicator variable, DriverIn was created to capture this response. This variable was coded as “1” if the respondent mentioned driver interviews in response to Question 9 and “0” if they did not. Similar variables were created for common qualitative answers to all the survey questions. Table 1 provides a list of all variables created using information from the telephone survey.

Table 1. Telephone survey variable list and coding

Related Survey Question Number	Variable Name	Variable Description	Coding
5	PubReg	Published rules and regulations for fatigued commercial motor vehicle drivers	1=Yes 0=No -999=Don't Know
5	FedReg	Mentioned federal regulations	1=Yes 0=No
5	StateReg	Mentioned specific state regulations	1=Yes 0=No
6	SpecProg	Specific program dealing with fatigued driving	1=Yes 0=No -999=Don't Know
6	FedProg	Mentioned federal programs	1=Yes 0=No
6	PSA	Mentioned public service announcements and education	1=Yes 0=No
6	OtherProg	Mentioned some other program	1=Yes 0=No
7	Train	Officers receive formal fatigue identification training	1=Yes 0=No -999=Don't Know
7	FedTrain	Mentioned federal training programs	1=Yes 0=No
7	OtherTra	Mentioned some other training program	1=Yes 0=No
8	Stop	Officers stop vehicles if they believe drivers are fatigued	1=Yes 0=No -999=Don't Know
9	StopFed	Mention federal regulations as part of stopped vehicle procedure	1=Yes 0=No
9	StopLog	Mention checking log books as part of stopped vehicle procedure	1=Yes 0=No
9	DriverIn	Mentioned driver interview as part of stopped vehicle procedure	1=Yes 0=No
9	CMVOos	Mentioned taking fatigued CMV driver out of service as part of stopped vehicle procedure	1=Yes 0=No
9	Driving	Mentioned driving cues as part of stopped vehicle procedure	1=Yes 0=No
9	Impair	Mentioned checking for drug, alcohol, etc. impairment first in stopped vehicle procedure	1=Yes 0=No

9	TrafficViol	Mentioned citing other traffic violations in stopped vehicle procedure	1=Yes 0=No
9	Discret	Mentioned officer discretion as part of stopped vehicle procedure	1=Yes 0=No
10	CrshLog	Mentioned checking log books as part of fatigue determination in a crash	1=Yes 0=No
10	CrshChar	Mentioned checking crash characteristics as part of fatigue determination in a crash	1=Yes 0=No
10	DrverState	Mentioned taking driver and witness statements as part of fatigue determination in a crash	1=Yes 0=No
10	Observ	Mentioned officer observations as part of fatigue determination in a crash	1=Yes 0=No
10	Recon	Mentioned crash reconstruction as part of fatigue determination in a crash	1=Yes 0=No

The telephone survey requested data related to fatigued driving enforcement procedures. Federal regulations only apply to commercial drivers so these techniques only apply to commercial drivers. The exception is Question 10 of the survey. Fatigue can be determined to be the cause of crash for all drivers.

4.2 FARS Data Analysis

The numbers of fatigue-involved fatal crashes were retrieved from the FARS database for each state from 2002 to 2010. The number of crashes was summed over the most recent five years and over all nine years to create variables for potential use in the crash frequency model. The nine year sum, F9Sum, was a better fit to the data and was used in the analysis. These sums consider all fatigue-involved fatal crashes, not just those of commercial drivers.

Fatigue-involved fatal crashes were chosen for the model as enforcement techniques are intended to create a safer driving environment by removing impaired drivers from the roadway. Therefore, such crashes are an objective way to model the fatigued driving aspect of roadway safety. Fatigue-involved fatal crashes may be less likely to suffer from reporting bias than less severe crashes as non-reporting probability is higher for less severe crashes. Some bias may be in the data as some states' enforcement officers may be more likely to list fatigue as the cause of a crash than others. Fatal crash information is readily available and therefore chosen for data analysis.

A crash frequency model may provide inconsistent results due to reporting bias in the data. To gain a better understanding of various states' reporting, descriptive statistics were calculated for the FARS data. These statistics primarily focused on the percentage of fatalities attributed to fatigue. The statistics are presented in the results section of this report.

4.3 HSIS Data Analysis

The HSIS database provides extensive information related to crashes and the road characteristics where they occurred for California, Illinois, Maine, Minnesota, and North Carolina. These data refer to all crashes attributed to fatigue which occurred in these states. There is no information available to differentiate crashes including commercial drivers.

The HSIS database provides crash data in four separate files: an accident file, a vehicle file, a road file, and an occupant file. The accident file provides a single record for each crash, the vehicle file provides a record for each vehicle involved in the accident, and the occupant file provides a record for each occupant involved in the crash. The road file provides information about roadway characteristics to be matched to the location of the crash presented in another file. Before a statistical model could be estimated, the files needed to be merged to form a usable spreadsheet with a single record for each crash.

Data were merged using the software, SAS (version 9.3). Only information from the road and accident files was necessary to output the desired data. Sample code used to merge the files for crashes in California in 2009 is presented in Appendix B. In some cases, the road file was too large to import as a single file into SAS 9.3 which limited the number of lines in a spreadsheet. The road file was split into a few smaller files and then matched with the crashes. Afterward, the files were small enough to merge back into a single file as only roadway information related to crash locations remained. Appendix C provides sample code for this situation.

After the files were merged, a few variables were recoded for different states. While each state provided information on crash injury severity, each state used a different numbering system to represent severity levels. The severity levels followed the KABCO scale used by law enforcement officers. An officer classifies the injury severity of a crash as one of five categories: K – killed, A – disabling injury, B – evident injury, C – possible injury (complaint of pain, and O – property damage only (no injury). While each state followed the KABCO scale in their records, they did not use the same values to represent each level so some had to be changed. Table 2 provides the variables taken from the HSIS database and their respective coding.

Table 2. HSIS database variables and coding

Variable Name	Variable Description	Coding
Aadt	Annual average daily traffic of roadway segment where crash occurred	Numerical value
Func1	Roadway segment where crash occurred is a principle arterial	1=Yes 0=No -999=Unknown functional class
Func2	Roadway segment where crash occurred is a minor arterial	1=Yes 0=No -999=Unknown functional class
Func3	Roadway segment where crash occurred is a major collector	1=Yes 0=No -999=Unknown functional class
Func4	Roadway segment where crash occurred is a minor collector	1=Yes 0=No -999=Unknown functional class
Func5	Roadway segment where crash occurred is a local road	1=Yes 0=No -999=Unknown functional class
Rodwy1	Roadway segment where crash occurred is an urban freeway with four or more lanes	1=Yes 0=No -999=Unknown roadway class
Rodwy2	Roadway segment where crash occurred is an urban freeway with less than four lanes	1=Yes 0=No -999=Unknown roadway class
Rodwy3	Roadway segment where crash occurred is an urban two lane road	1=Yes 0=No -999=Unknown roadway class
Rodwy4	Roadway segment where crash occurred is an urban multilane divided non-freeway	1=Yes 0=No -999=Unknown roadway class
Rodwy5	Roadway segment where crash occurred is an urban multilane undivided non-freeway	1=Yes 0=No -999=Unknown roadway class
Rodwy6	Roadway segment where crash occurred is a rural freeway with four or more lanes	1=Yes 0=No -999=Unknown roadway class
Rodwy7	Roadway segment where crash occurred is a rural freeway with less than four lanes	1=Yes 0=No -999=Unknown roadway class
Rodwy8	Roadway segment where crash occurred is a rural two lane road	1=Yes 0=No -999=Unknown roadway class

Rodwy9	Roadway segment where crash occurred is a rural multilane divided non-freeway	1=Yes 0=No -999=Unknown roadway class
Rodwy10	Roadway segment where crash occurred is a rural multilane undivided non-freeway	1=Yes 0=No -999=Unknown roadway class
Urban	Crash occurred in urban location	1=Yes 0=No -999=Unknown
Crshsev	Severity of crash	0=Property damage only 1=C-type injury 2=B-type injury 3=A-type injury 4=Fatal crash
Yr2006	Crash occurred in 2006	1=Yes 0=No
Yr2007	Crash occurred in 2007	1=Yes 0=No
Yr2008	Crash occurred in 2008	1=Yes 0=No
Yr2009	Crash occurred in 2009	1=Yes 0=No
Yr2010	Crash occurred in 2010	1=Yes 0=No
Yr2011	Crash occurred in 2011	1=Yes 0=No
Spring	Crash occurred in spring season	1=Yes 0=No
Summer	Crash occurred in summer season	1=Yes 0=No
Fall	Crash occurred in fall season	1=Yes 0=No
Winter	Crash occurred in winter season	1=Yes 0=No
Numvehs	Number of vehicles involved in crash	Numerical value

4.4 Other Data Sources

Additional data were retrieved to allow for other variables to be included in the model estimation. Vehicle miles traveled data were retrieved from the Federal Highway

Administration (FHWA) website for the same years over which FARS data was retrieved. Vehicle miles traveled was included in the analysis as an exposure variable as more crashes were expected in states where more driving occurred. Vehicle miles traveled data include the number of miles driven by all drivers, not just commercial drivers. Data were also retrieved from the Federal Motor Carrier Safety Administration (FMCSA) online Summary of Roadside Inspections. Information regarding the number of commercial motor vehicle inspections and the rate at which officers removed drivers from the road were retrieved. Table 3 provides the variables created from the information from FHWA and FMCSA.

Table 3. Additional variables and coding

Variable Name	Variable Description	Coding
Inspec	Number of commercial vehicle inspections in fiscal year 2011	Numerical value
LnInspec	Natural log of number of commercial vehicle inspections in fiscal year 2011	Numerical value
DOosR	Driver inspection out of service rate in fiscal year 2011	Numerical value
VoosR	Vehicle inspection out of service rate in fiscal year 2011	Numerical value
V9Sum	Sum of VMT (in millions) from 2002 to 2010	Numerical value
LnV9	Natural log of sum of VMT from 2002 to 2010	Numerical value
V5Sum	Sum of VMT (in millions) from 2006 to 2010	Numerical value
LnV5	Natural log of sum of VMT from 2006 to 2010	Numerical value

A complete list of all variables considered when estimating the statistical models is included in Appendix D.

4.5 Crash Frequency Model Estimation

To analyze the safety effects of various enforcement techniques, statistical models were estimated. Two crash frequency models were estimated. The first model used data from the FARS database and the second model used data from the HSIS database. In both cases, the results from the telephone survey and the data from FHWA and FMCSA were considered as independent variables.

Both crash frequency models were negative binomial models. A Poisson model is traditionally used to model safety due to the random nature of crashes. A Poisson regression model has been widely used to study count data with generally small values. Crashes are count data as it is impossible to record a partial crash. As crashes are rare, random events, a Poisson model is appropriate. All models are estimated in the software program, NLOGIT (version 4.0).

4.5.1 FARS Crash Frequency Model Estimation

A crash frequency model was estimated with data from the FARS database. The sum of fatigue-involved fatal crashes, F9Sum, for each state was used as the dependent variable. Data from each state were considered one observation for a total of 49. The analysis process began by modeling each variable with a vehicle miles traveled variable, V9Sum. Variables which were statistically significant at a 95% confidence level remained in consideration for the final model.

The trial period of individual variables made it obvious the nine-year sum of vehicle miles traveled and fatigue-involved fatal crashes were a better choice for the model. Therefore, V9Sum was used as an independent variable and F9Sum was used as the dependent variable in the final model. For both vehicle miles traveled and the number of commercial motor vehicle inspections, the natural logarithmic transformation was also considered. For vehicle miles traveled, the non-transformed variable gave a better fit than the model with the log-transformed variables. The fit was judged with the McFadden's pseudo r-squared value.

Model estimation began by including variables which were statistically significant at a 95% confidence level when modeled on their own. The remaining variables were added one by one. If a variable was statistically significant at a 95% confidence level when modeled on its own and was no longer statistically significant after another variable was added, it was removed from the model. This change implied the variable was not independent of the others and should not be included.

Upon further inspection, certain variables were excluded from the model. All variables related to Question 10 in the survey, how fatigue is determined as the cause of the crash, were excluded from the analysis because these variables describe the situation after a crash had already occurred. The procedure after a crash will not impact the likelihood of a future crash. The only plausible relationship would be an increased number of crashes if certain identification techniques were used. These procedures may make it more likely fatigue would be correctly identified as the cause of the crash. Instead of affecting the actual number of crashes, these procedures may affect the reporting of a crash. This relationship was not seen in the analysis so these variables were excluded from the final model. Also, variables related to federal regulations and federally administered training were excluded as all states abide by federal rules and regulations and there was no variation in the data. A final model was estimated taking into account the statistical significance of each variable and the McFadden's pseudo r-squared value. The McFadden's pseudo r-squared value is calculated by NLOGIT and is a measure of goodness of fit. It can range from zero to one with a value closer to one implying the model is a better fit to the data. The estimated model is presented in Section 5.3.1.

4.5.2 HSIS Crash Frequency Model Estimation

A second crash frequency model was estimated using data pertaining to four states for a period of five years from the HSIS database. These four states were California, Illinois, Minnesota, and North Carolina. Data were also retrieved from Maine but only three years of data were available. Considering each year of data for each state as an observation, 23 observations were used in the model estimation. As with the FARS model, responses from the telephone survey were used as independent variables. The sum of fatigue-involved crashes, NumCrsh, was used as the dependent variable. Unlike the FARS model which was based on fatigue-involved fatal crashes only, this model included all crashes attributed to fatigue. While information from the HSIS database was retrieved specifically for estimation of a crash severity model, a crash frequency model was estimated to gain better understanding of the effect of enforcement.

The model estimation began by modeling each variable with the vehicle miles traveled variable, VMT. VMT is the yearly vehicle miles traveled in that state. If the variable was statistically significant at a 95% confidence level, it remained in consideration for the final model. Next, the remaining variables were added one by one to those previously found to be statistically significant. If a variable was statistically significant at a 95% confidence level when modeled on its own and no longer statistically significant with the addition of other variables, it was removed as this implies it is not independent of the other variables.

Similar to the FARS model, data pertaining to Question 10 and those related to federal regulations and training were excluded for the same reasons as discussed for the FARS model. But, other variables needed to be excluded as well. With the smaller sample size, some variables were collinear across the observations. These were: PubReg, PSA, OtherProg, TrafficViol, DrverState, and Observ. These variables could not be modeled with the HSIS data and were therefore excluded from the model specification.

A final model was estimated taking into account the significance of the included variables and the McFadden pseudo r-squared value. The final model is presented in Section 5.3.2 of this report.

4.6 Crash Severity Model Estimation

An ordered probit crash frequency model was estimated using information from the HSIS database. An ordered probit model was chosen as it is a traditional choice for ordinal crash severity and is easy to interpret. The reviewed literature suggested ordered probit models may provide the best results for a small sample size and limited data detail. More complex models exist such as multinomial logit, nested logit, and bivariate ordered probit models but are normally compared to ordered probit or logit models.

Crash severity is a continuous variable but is treated as an ordinal variable when categorized with the KABCO scale. Crash severity can be numerically compared but the comparison is not meaningful. For example, it cannot be said that a fatal crash is twice as severe as a crash with incapacitating injuries. The HSIS database follows the KABCO scale used by law enforcement officers for recording crash injury severity. An officer classifies the injury severity as one of five categories: K – killed, A – disabling injury, B – evident injury, C – possible injury, and O – no apparent injury. While each state followed the KABCO in their records, they did not use the same values to represent each level so some had to be changed as described in Section 4.3.

An ordered probit model is built around a latent regression. A latent regression utilizes a continuous instead of a discrete predictor. The form is derived from the following equation (Greene, 2008):

$$y^* = x'\beta + \varepsilon$$

In this case, y^* is an unobserved variable, β is the vector of regression coefficients, and x' is the vector of independent variables. The following situations are observed for J categories:

$$y = 0 \; if \; y^* \leq 0$$

$$y = 1 \; if \; 0 < y < \mu_1$$

$$y = 2 \; if \; \mu_1 < y^* < \mu_2$$

$$\vdots$$

$$y = J \; if \; \mu_{J-1} \leq y^*$$

The μ values are unknown parameters estimated with β. As all outcomes are required to belong to a specific category, there are errors associated with estimation (while crash severity is listed as one of five categories there is still adjustment necessary to assign a wide variety of potential injuries to one of these severity levels). The value ε is this error and is assumed to be normally distributed (Greene, 2008).

5.0 RESULTS

The following sections detail the results found from the previously discussed data analysis techniques. Results are provided for the telephone survey responses, descriptive statistics from the FARS data, and the three crash models.

5.1 Telephone Survey Results

The telephone survey results were summarized. In the case of qualitative responses, they were grouped by theme to provide a better understanding of various states' policies and procedures related to fatigue. The following section provides Geographic Information System (GIS) figures produced in the software program ArcMap 10. The figures illustrate states' responses to the "yes" or "no" survey questions. Below each figure, any qualitative responses with more than one occurrence are provided from most to least common. The responses may add up to more than 49 because a single agency may have mentioned multiple procedures in response to a single question.

Question 5. Does your agency have published rules and regulations dealing with the issue of fatigue in commercial motor vehicle drivers?

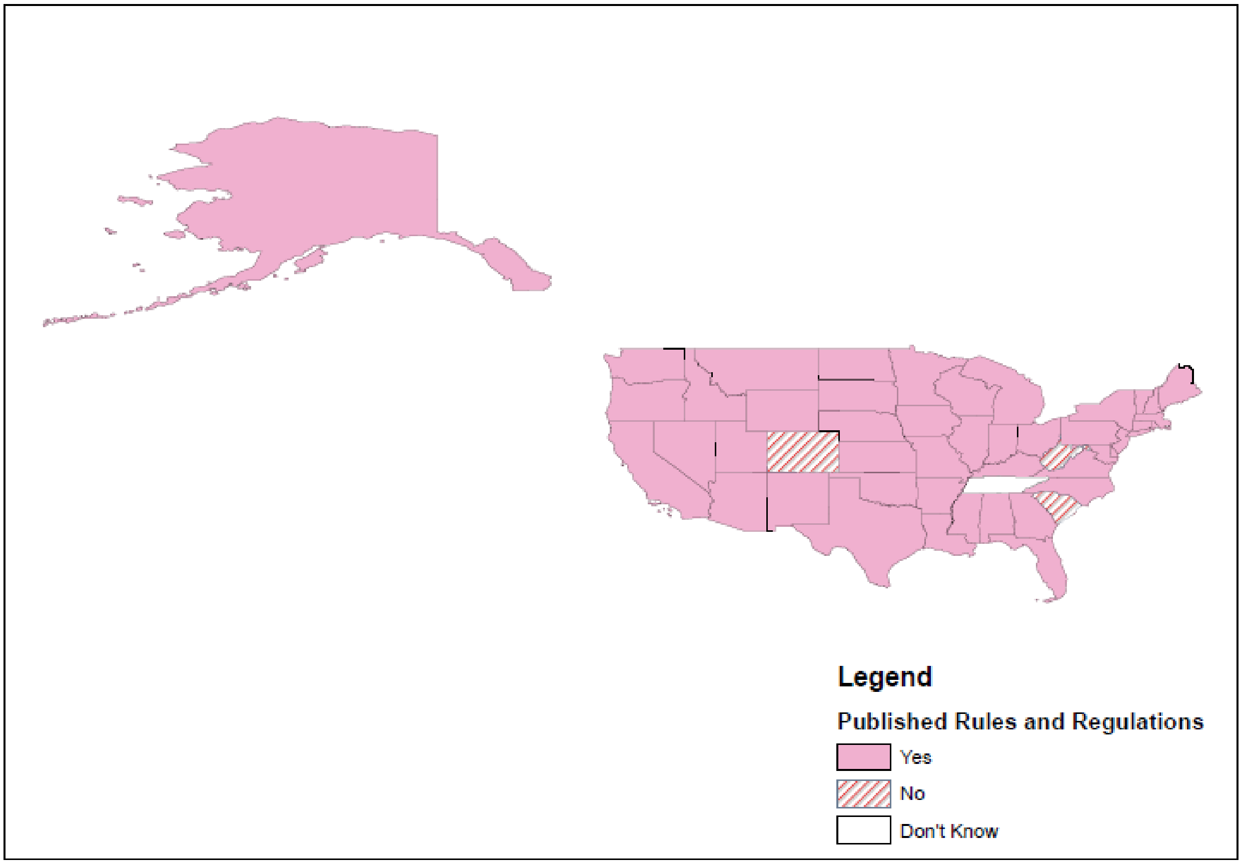

Figure 2. Question 5 responses

Yes – 45
No – 3
Don't Know – 1

Qualitative Responses:
Federal regulations – 43
State regulations – 7

Question 6. Does your agency have any specific program that deals with the issues of fatigued motor vehicle drivers?

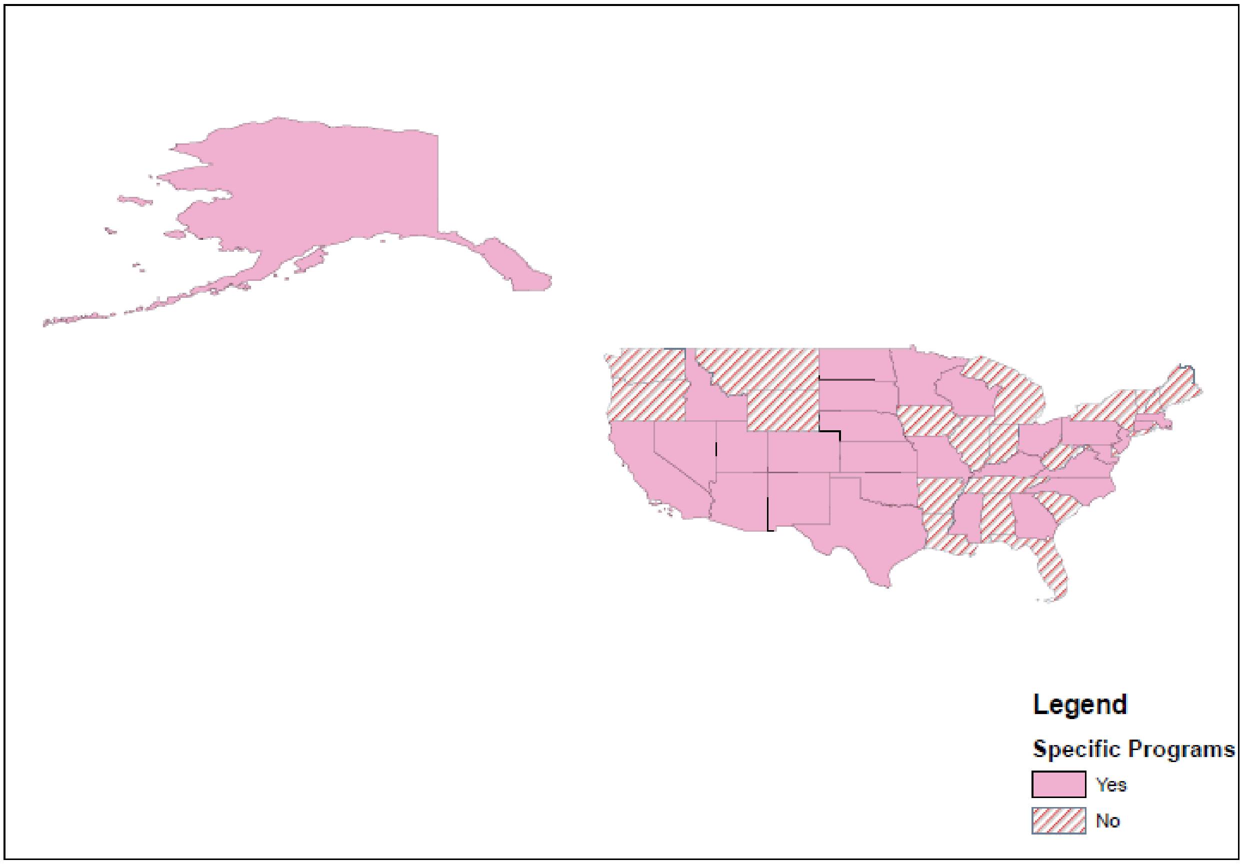

Figure 3. Question 6 responses

Yes – 28
No – 21

Qualitative Responses:
Federal regulations and inspection criteria – 15
Public outreach and education – 8
Other programs – 7

Seven states responded to Question 6 by mentioning other programs which did not fit into the categories of federal regulations or public outreach and education. These were: Arizona, Connecticut, Florida, Georgia, Idaho, Kansas, and Oklahoma. Each state's response is shown below to provide more information about other types of fatigue driving programs. No further explanation about the program was given other than what is provided below.

Arizona: Defeating Distracted Driving

Connecticut: Motor Vehicle Assistance Program

Florida: Work in conjunction with DUI checkpoints

Georgia: Targeting Aggressive Cars and Trucks

Idaho: Specific regulations for farmer-based products

Kansas: Quarterly rotating training which includes an out of service unit

Oklahoma: Driver behavior training

Question 7. Do officers in your agency receive formal training identifying fatigue in motor vehicle drivers?

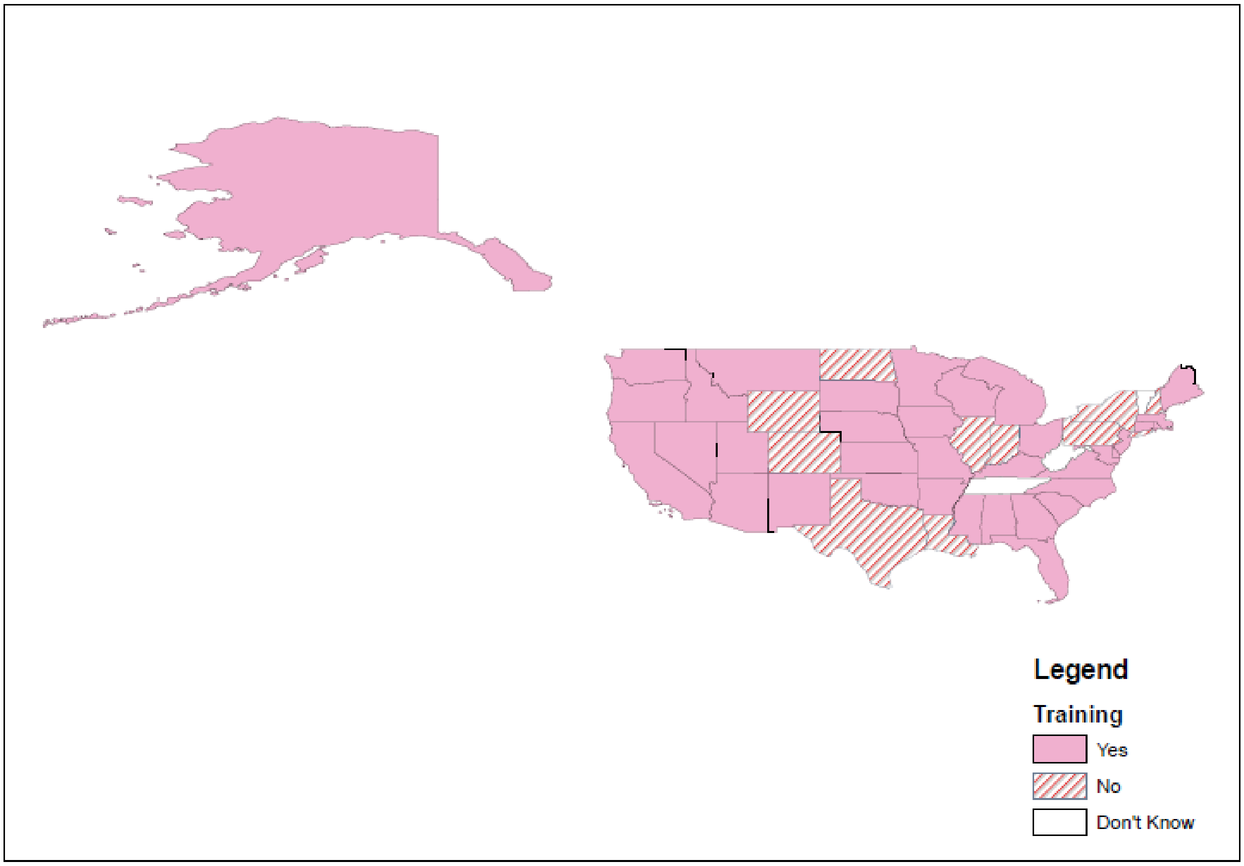

Figure 4. Question 7 responses

Yes – 36
No – 10
Don't Know – 3

Qualitative Responses:
Federal training for North American Standard Level 1 Inspection – 27
Other training – 14

Question 8. Do officers in your agency stop vehicles if they believe drivers are fatigued?

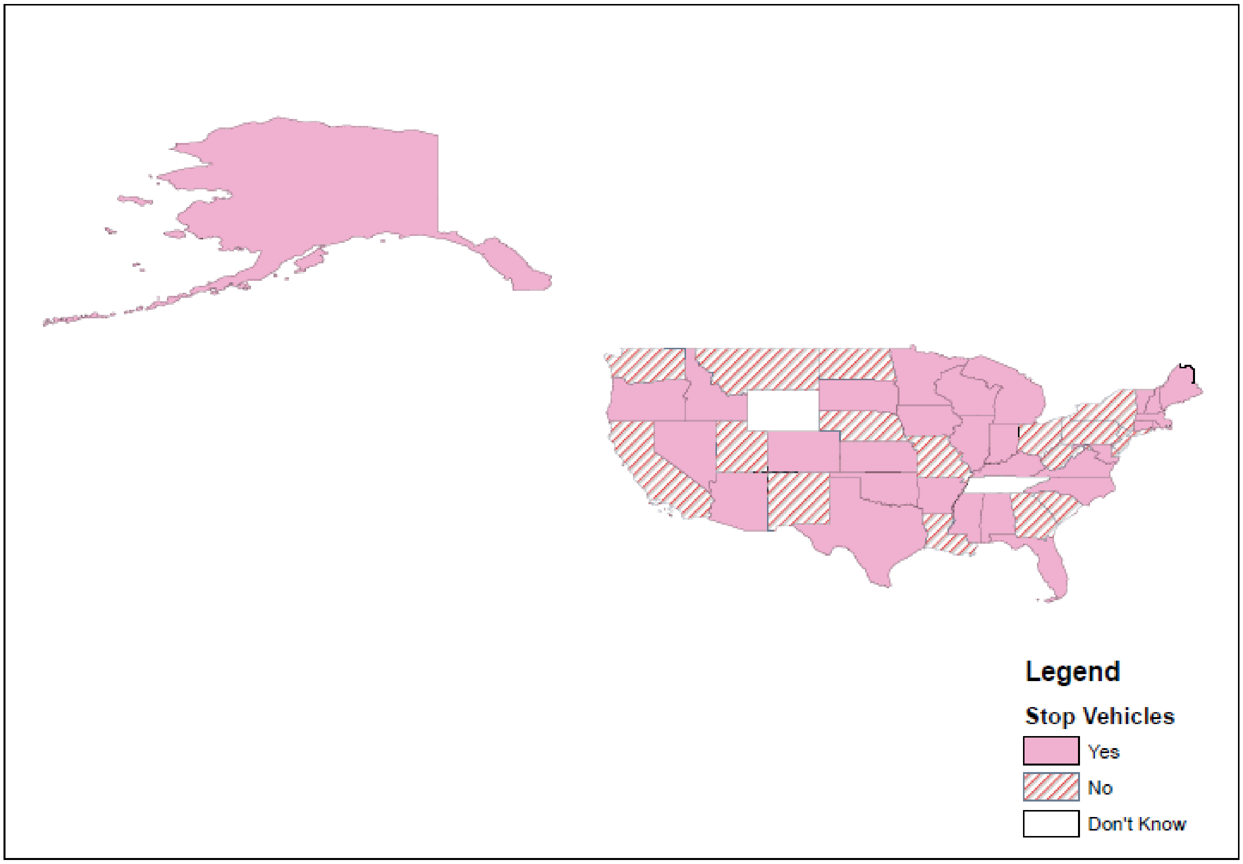

Figure 5. Question 8 responses

Yes – 30
No – 17
Don't Know – 2

Question 9. What procedure is followed when an officer stops a driver believed to be fatigued?

Place CMV out of service – 21
Driver interview/behavior – 18
Check for other impairments – 17
Check log books and driving times – 15
Officer discretion – 11
Federal regulations – 8
Enforce other traffic violations – 6
Driving cues – 5

Question 10. How is fatigue determined to be an issue in a motor vehicle crash?

Driver/witness statements – 30
Log books – 19
Crash characteristics – 10
Officer observations – 6
Crash reconstruction – 4

In addition to the questions shown above, the survey requested statistics related to the number of CMV inspections, any legally challenged fatigue citations, and the number of fatigue-attributed crashes (Questions 11-16, as shown in Appendix A). Relatively few states responded to these questions as the respondents did not know the answers or the states did not track statistics in this manner. These questions were not considered in the crash models due to the low response rate. Instead, CMV inspection information for 2011 was retrieved from the Federal Motor Carrier Safety Administration website. Figure 6 provides a map of the number of CMV inspections.

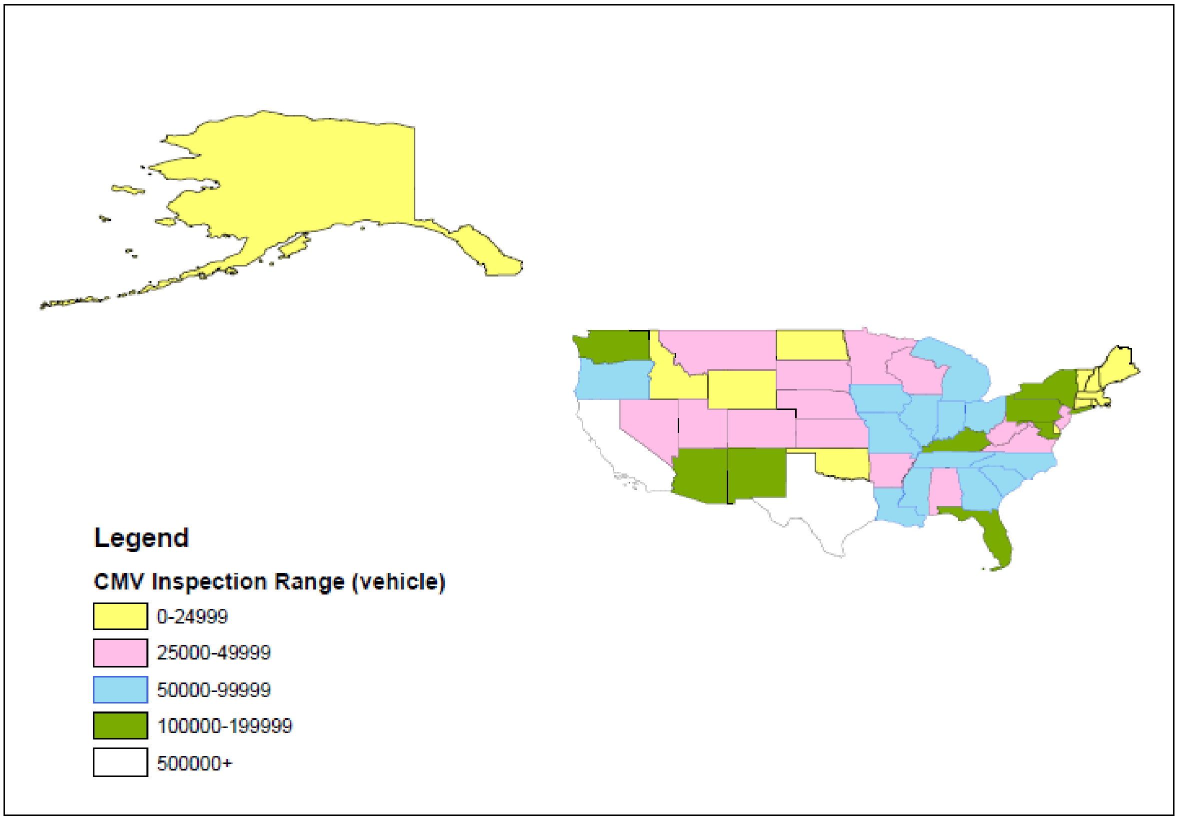

Figure 6. 2011 CMV roadside inspections

Reponses to Question 10, “How is fatigue determined to be an issue in a motor vehicle crash?”, made it apparent enforcement agencies have issues recognizing fatigue. Arkansas officials responded there is “no way” to do so effectively. Utah officials stated, they “probably miss many times” fatigue as the cause of a crash. Five agencies stated “driver admission” is the only way they can determine fatigue to be the cause. State patrol officers are not able to effectively determine fatigue as the cause of a crash.

5.2 FARS Data Statistics

Descriptive statistics were calculated for the FARS data to gain a better understanding of states’ enforcement agencies reporting of fatigued driving. The crash data obtained from the FARS database were crashes attributed to fatigue through police reports. Officers in some states may be more likely to consider fatigue as a cause of a crash than others so these statistics help to identify states with high or low rates of fatigue reporting in fatal crashes. Differences in the rate of identifying fatigue as a crash causing factor amongst various agencies may be introducing bias into the data. This is especially likely due to the lack of objective means for identifying fatigue.

Between 2002 and 2010, a total of 360,393 fatalities were reported in the US. Of these, 13,187 (2.68%) were attributed to fatigue. While one state may have more fatigued drivers than another because of its geography and the locations of commercial driving hubs, the nationwide average is a good baseline with which to compare each state's percentage of fatal crashes attributed to fatigue. There is no reason to believe the percentage of fatal crashes caused by fatigued will vary significantly across the country.

Table 4 presents descriptive statistics related to the number of fatigue-involved fatal crashes which occurred in each state. Averages and standard deviations are rounded to full crashes. The percent of crashes attributed to fatigue is a better indicator than the number of fatigue-involved fatal crashes as some states have significantly more crashes than others simply due to a larger population and greater highway miles. The national average is shown as a baseline for comparing individual states' percentages. Table 5 details information related to the percentages of fatalities attributed to fatigue. The "Actual Percent of Fatalities Attributed to Fatigue" was calculated by summing the number of fatigue-involved fatal crashes and dividing by the total number of fatal crashes over the time period. The "Yearly Percentages Average" was calculated by summing each year's percent of fatal crashes attributed to fatigue for a single state. This value was then divided by the number of years of data. It is simply an average of these percentages.

The "Yearly Percentages Weighted Average" was calculated by summing the product of the number of fatigue-involved fatal crashes by the percentage of fatal crashes attributed to fatigue for a single state. This value was then divided by the total number of fatigue-involved fatal crashes. It is an average of the percentage of fatal crashes attributed to fatigue, weighted by the number of fatigue-involved fatal crashes.

Table 4. Fatigue fatalities statistics (2002 – 2010) (source: FARS)

State	Total Fatalities	Total Fatigue Attributed Fatalities	Minimum Fatigue Fatalities in One Year	Maximum Fatigue Fatalities in One Year	Average Fatigue Fatalities	Standard Deviation of Fatigue Fatalities
US	402589	14877	1202	1693	1465	183
Alabama	10331	528	31	69	52	11
Alaska	788	29	2	4	3	1
Arizona	10501	436	27	61	42	12
Arkansas	6321	131	8	21	13	4
California	38195	936	57	123	88	27
Colorado	5949	497	34	75	49	13
Connecticut	2965	127	4	17	12	4
Delaware	1272	74	4	11	8	3
Florida	30634	175	7	30	17	9
Georgia	15502	485	34	60	49	9
Hawaii	1302	53	3	9	6	2
Idaho	2537	205	17	30	21	5
Illinois	12389	391	18	54	40	14
Indiana	8486	374	24	49	35	8
Iowa	4190	41	1	9	4	2
Kansas	4442	287	15	40	28	8
Kentucky	8790	391	33	47	39	6
Louisiana	9119	236	9	40	24	12
Maine	1824	143	3	24	13	7
Maryland	6126	247	16	30	23	5
Massachusetts	4196	268	12	49	25	11
Michigan	11143	138	6	20	13	5
Minnesota	5297	118	4	16	11	4
Mississippi	8291	93	1	22	10	7
Missouri	10670	493	24	69	49	16
Montana	2421	232	8	36	21	10
Nebraska	2522	58	2	7	5	2
Nevada	3513	134	9	21	13	4
New Hampshire	1365	103	4	17	10	5
New Jersey	6944	195	11	28	19	5
New Mexico	4331	108	2	22	12	8
New York	13898	639	47	75	62	8
North Carolina	15069	103	4	27	11	7
North Dakota	1101	48	1	10	3	3

Ohio	12463	121	6	24	11	6
Oklahoma	7355	316	18	46	33	10
Oregon	4422	189	12	24	18	4
Pennsylvania	14893	510	28	67	53	12
Rhode Island	803	54	3	11	6	2
South Carolina	9969	374	26	53	39	8
South Dakota	1666	76	4	14	8	4
Tennessee	11785	385	28	57	39	10
Texas	35190	2865	221	336	283	44
Utah	2848	271	10	46	27	12
Vermont	781	69	3	13	6	3
Virginia	8973	231	17	35	24	7
Washington	5798	324	11	43	31	11
West Virginia	3885	131	7	20	13	4
Wisconsin	7239	154	6	28	17	8
Wyoming	1654	189	10	26	18	5

Table 5. Fatigue fatalities percentages statistics (2002-2010) (source: FARS)

State	Actual Percent of Fatalities Attributed to Fatigue	Yearly Percentages Average	Yearly Percentages Weighted Average	Standard Deviation of Percentages	Minimum of Yearly Percentages	Maximum of Yearly Percentages
US	3.66	3.66	3.67	0.25	3.28	4.03
Alabama	5.03	5.00	5.13	0.75	3.66	5.98
Alaska	3.58	3.64	3.74	0.77	1.98	4.69
Arizona	4.03	4.01	4.18	0.80	2.52	5.17
Arkansas	2.05	2.05	2.25	0.68	1.23	3.21
California	2.32	2.30	2.42	0.50	1.65	2.96
Colorado	8.45	8.35	8.54	0.87	7.31	10.09
Connecticut	4.19	4.15	4.46	1.20	1.79	5.76
Delaware	5.99	5.96	6.47	1.83	3.76	8.62
Dist. Columb.	1.88	1.89	4.01	2.37	0.00	6.90
Florida	0.56	0.55	0.66	0.26	0.24	0.92
Georgia	3.15	3.19	3.28	0.69	2.36	4.64
Hawaii	4.39	4.38	4.67	1.16	2.26	6.52
Idaho	8.30	8.27	8.56	1.53	6.44	10.24
Illinois	3.24	3.17	3.40	0.80	1.92	4.31
Indiana	4.13	4.16	4.36	1.06	3.34	6.50
Iowa	0.93	0.94	1.28	0.60	0.22	2.22
Kansas	6.28	6.25	6.69	1.68	3.91	8.53
Kentucky	4.43	4.46	4.54	0.74	3.56	5.69
Louisiana	2.64	2.68	3.24	1.35	0.96	4.85
Maine	7.35	7.15	8.58	3.23	1.86	12.37
Maryland	3.82	3.86	4.06	1.06	2.71	6.09
Massachusetts	6.05	5.91	6.74	2.14	3.53	10.68
Michigan	1.19	1.24	1.46	0.62	0.52	2.29
Minnesota	2.03	2.08	2.36	0.92	0.81	3.65
Mississippi	1.23	1.22	1.73	0.82	0.11	2.41
Missouri	4.65	4.54	4.81	0.95	2.93	5.49
Montana	8.81	8.59	10.07	3.61	4.23	13.74
Nebraska	1.93	1.89	2.08	0.58	0.90	2.54
Nevada	3.78	3.88	4.08	1.15	2.09	5.76
New Hampshire	7.20	7.11	8.47	3.25	2.90	13.39
New Jersey	2.82	2.90	3.12	1.02	1.47	5.04
New Mexico	2.43	2.37	3.72	1.89	0.00	5.08
New York	4.52	4.52	4.54	0.31	4.06	5.03
North Carolina	0.71	0.73	1.07	0.56	0.26	2.05

North Dakota	3.01	3.12	5.27	2.92	0.95	10.31
Ohio	0.88	0.88	1.12	0.48	0.45	1.69
Oklahoma	4.41	4.41	4.75	1.34	2.69	6.86
Oregon	4.22	4.30	4.45	1.03	2.34	5.36
Pennsylvania	3.56	3.60	3.80	0.98	1.73	5.06
Rhode Island	7.06	6.94	7.71	2.18	3.61	10.58
South Carolina	3.95	3.94	4.05	0.66	2.91	5.03
South Dakota	4.15	3.97	5.08	2.12	0.00	7.33
Tennessee	3.37	3.35	3.47	0.62	2.38	4.49
Texas	8.11	8.08	8.17	0.72	7.21	9.00
Utah	9.46	9.24	10.70	3.62	4.18	14.02
Vermont	8.42	8.12	9.67	3.33	4.23	13.27
Virginia	2.65	2.74	3.01	1.09	1.77	4.73
Washington	5.44	5.35	5.83	1.61	2.11	7.53
West Virginia	3.31	3.32	3.64	1.11	1.62	5.35
Wisconsin	2.32	2.50	3.17	1.57	0.75	4.99
Wyoming	11.31	11.26	12.02	3.05	6.29	14.77

Using the weighted average percentage of fatalities attributed to fatigue between 2002 and 2009, the states with the lowest and highest rates of fatigue-involved fatal crashes were identified. They are shown in Tables 6 and 7, respectively.

Table 6. Ten states with lowest percentages of crashes attributed to fatigue (source: FARS)

State	Yearly Percentages Weighted Average	Minimum of Yearly Percentages	Maximum of Yearly Percentages
Florida	0.55	0.24	0.92
North Carolina	1.07	0.26	2.05
Ohio	1.12	0.45	1.69
Iowa	1.28	0.22	2.22
Michigan	1.46	0.52	2.29
Mississippi	1.73	0.11	2.41
Nebraska	2.08	0.90	2.54
Arkansas	2.25	1.23	3.21
Minnesota	2.36	0.81	3.65
California	2.42	1.65	2.96

Table 7. Ten states with highest percentages of crashes attributed to fatigue (source: FARS)

State	Yearly Percentages Weighted Average	Minimum of Yearly Percentages	Maximum of Yearly Percentages
Rhode Island	7.71	3.61	10.58
Texas	8.17	7.21	9.00
New Hampshire	8.47	2.90	13.39
Colorado	8.54	7.31	10.09
Idaho	8.56	6.44	10.24
Maine	8.58	1.86	12.37
Vermont	9.67	4.23	13.27
Montana	10.07	4.23	13.74
Utah	10.70	4.18	14.02
Wyoming	12.02	6.29	14.77

As shown by Tables 6 and 7, the average percentage of fatal crashes attributed to fatigue varies between states from 0.55% to 12.02%. This is a noticeable variation from the smallest to the largest. It is unlikely that fatal crashes in Wyoming are 20 times more likely to be caused by fatigue than those in Florida. This shows there is probable bias in the reporting of fatigue as a crash cause in fatal crashes.

These 20 states' yearly percentages were then graphed to visually present their variations over time. These figures were created to see if there was any noticeable pattern across different states of how the percentage of fatigue-involved fatal crashes changes. Figures 7 and 8 present the graphs for the states with the lowest and highest percentages, respectively. The national percentage is included for comparison.

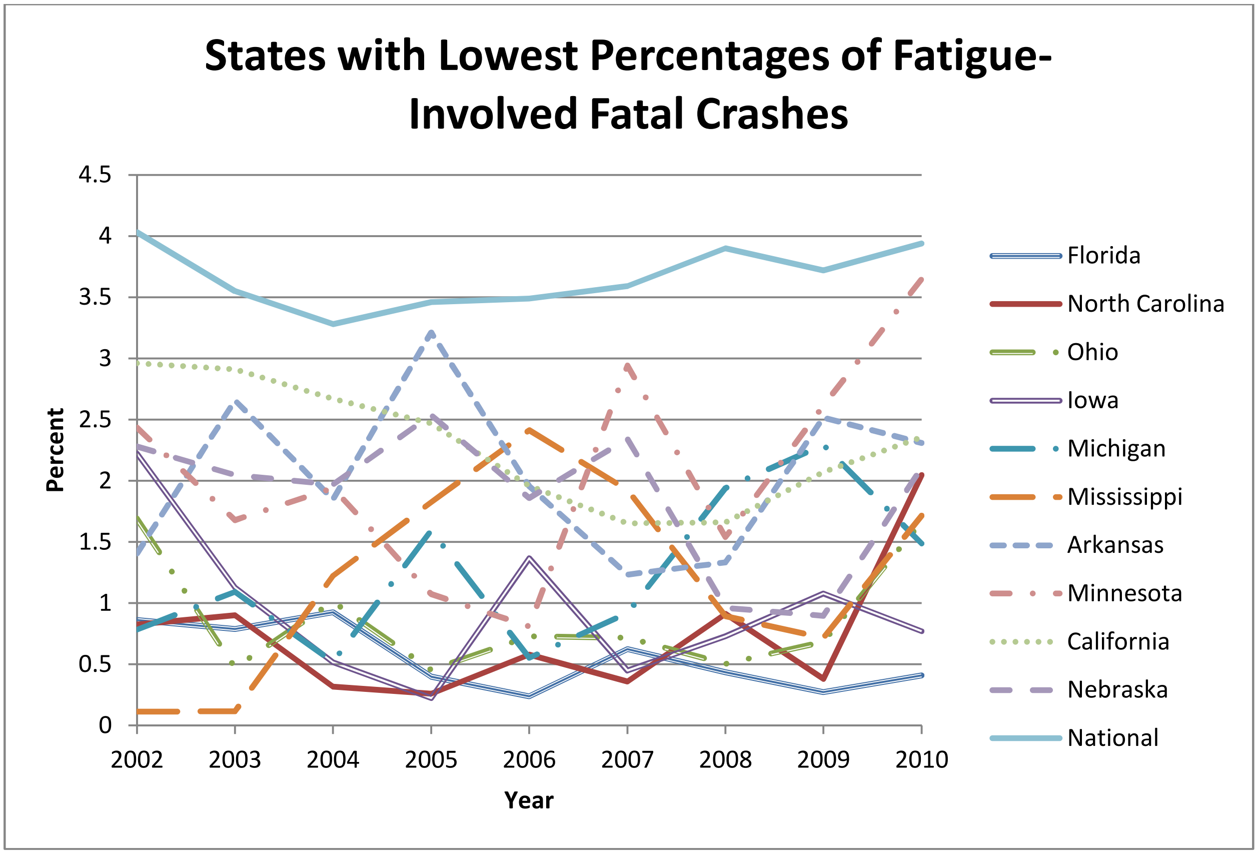

Figure 7. Percentage of fatigue-involved fatal crashes for states with the lowest averages from 2002 to 2010

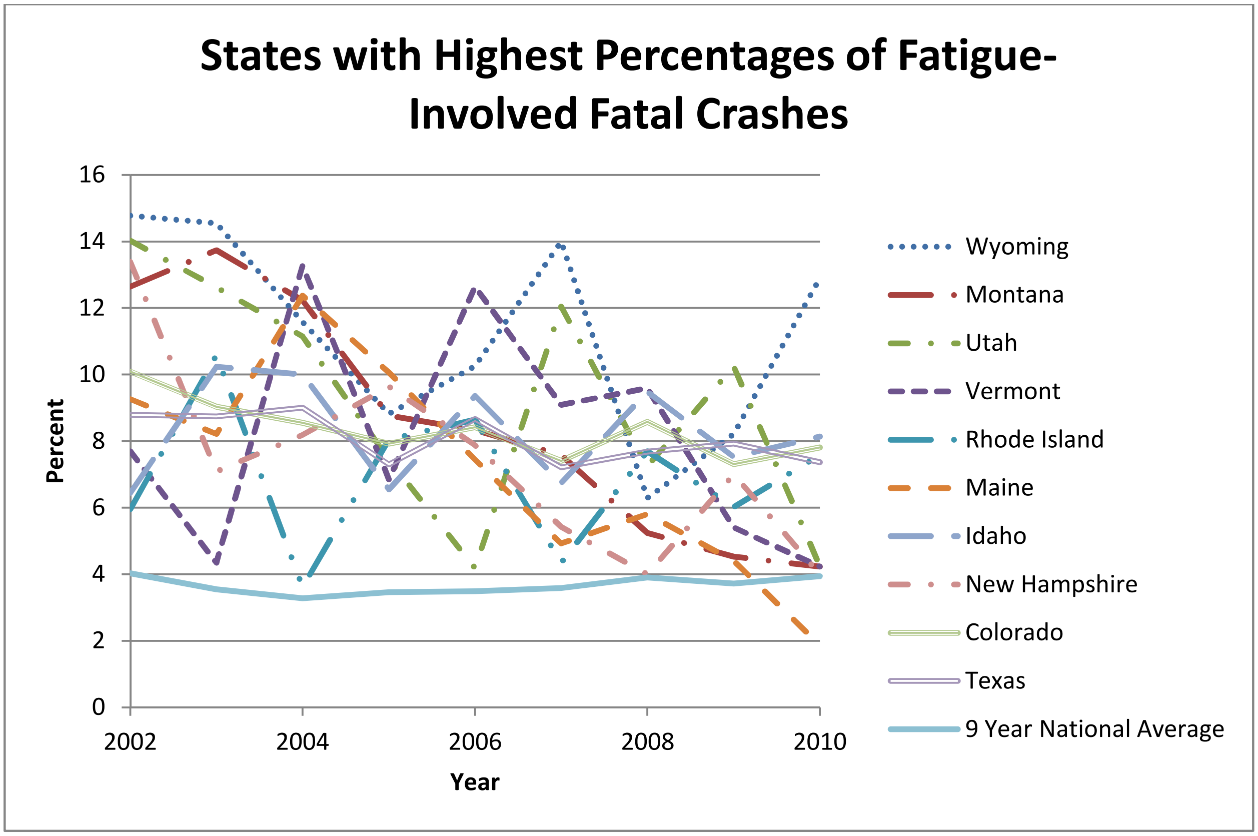

Figure 8. Percentage of fatigue-involved fatal crashes for states with the highest averages from 2002 to 2010

No discernible pattern is seen in either figure. Hours of Service (HOS) regulations have changed over this time period (2002-2010). In 2003, regulations were introduced which increased the time a driver could drive, but reduced the amount of allowable on-duty time. This regulation was overturned by the US Court of Appeals, but a similar regulation was introduced in 2005. This regulation reintroduced the same drive times used in the 2003 regulation and included a change which required driver to use their sleeper berth for eight consecutive hours. The HOS regulations were again changed in 2007. This change affected a driver’s ability to restart after being off-duty (Werner Enterprises). These figures make it appear that the updates to the regulations are not affecting the number of fatigue-involved fatal crashes. As no pattern can be ascertained visually from figures 7 and 8, no further analysis was carried out with these data.

5.3 Crash Frequency Model Results

The following sections present the final crash frequency models estimated using data from the telephone survey, FARS database, and HSIS database.

5.3.1 FARS Crash Frequency Model Results

As previously described (Section 4.5.1), a negative binomial model was estimated using data from the FARS database. Table 8 presents the final model parameters. The nine-year sum of fatigue-involved fatal crashes, F9Sum, was used as the dependent variable. The McFadden's pseudo r-squared value was 0.8715940.

Table 8. Estimated model parameters for FARS data crash frequency model

Variable	Coefficient	Significance (p-value)	Mean	Marginal Effect
Constant	5.70376888	0.0000	N/A	1558.26966
V9Sum	0.788515D-06	0.0000	557910.178	0.00021542
Train	-0.86683568	0.0003	0.80000000	-236.819508
PSA	-0.23849687	0.2440	0.17777778	-65.1573437
Driving	-0.65548262	0.0473	0.11111111	-179.077853

The equation for the estimated model is of the form:

$$F9Sum = e^{(0.7885\times 10^{-6} V9Sum - 0.8668 Train - 0.2385 PSA - 0.6555 Driving + 5.7308)}$$

The complete model estimation output from NLOGIT software is shown in Appendix E.

5.3.2 HSIS Crash Frequency Model Results

A negative binomial model was estimated using data from the HSIS database. Table 9 shows the final model parameters. In this model, each year of data for each state was considered as an observation. The dependent variable, NumCrsh, is the number of fatigue-involved crashes reported in a specific year. The McFadden's pseudo r-squared value was 0.5202498.

Table 9. Estimated model parameters for HSIS data crash frequency model

Variable	Coefficient	Significance (p-value)	Mean	Marginal Effect
Constant	5.76808582	0.0000	N/A	4953.72299
VMT	0.660541D-05	0.0000	131048.304	0.00567283
SpecProg	-0.19794173	0.0276	0.65217391	-169.995476
DriverIn	-0.13161595	0.1607	0.34782609	-113.033851

The equation for the estimated model is of the form:

$$NumCrsh = e^{(0.6605\times10^{-5}VMT - 0.1979SpecProg - 0.1316DriverIn + 5.7681)}$$

The complete model estimation output from NLOGIT software is shown in Appendix F.

5.4 Crash Severity Model Results

An ordered probit model was estimated to analyze the effect fatigued driving enforcement techniques have on crash severity. Crash severity was represented by five categories: K – killed, A – disabling injury, B – evident injury, C – possible injury, and O – property damage only. A crash with no injuries was considered to be the lowest category and assigned a value of zero. A fatal crash was assigned a value of four in the analysis data. To separate the five categories, the ordered probit model estimates threshold values which separate the categories. Figure 9 graphically represents the threshold values. The software program NLOGIT sets the first threshold value to be zero.

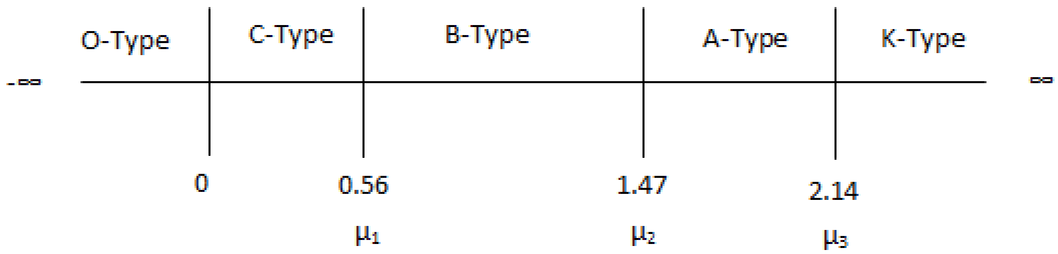

Figure 9. HSIS crash severity model threshold values

A crash is determined to be of a specific crash severity category based on the sum of model parameters times their specific estimated coefficients. Table 10 provides the final model coefficients and significant variables.

Table 10. Estimated model parameters for HSIS data crash severity model

Variable	**Coefficient**	**Significance (p-value)**
Constant	-0.15141842	0.0000
Driving	-0.17643818	0.0000
Winter	-0.07060437	0.0006
Func1	0.04981127	0.0134
Stop	-0.02493353	0.2366

The complete output from NLOGIT is available in Appendix G.

6.0 MODEL DISCUSSION

The following sections describe the statistical models estimated using information from the telephone survey and the various other data sources. Statistically significant independent variables are discussed to describe how they affect the dependent variable and which fatigued driving enforcement techniques may have a positive impact on roadway safety.

The variable coefficients imply some positive and some negative correlations with fatigue-involved crashes. A positive coefficient implies a positive correlation with crashes. In the case of the crash frequency models, as the value of the independent variable increases, the expected number of fatigue-involved crashes increases. A negative coefficient implies the opposite; as the value of the variable increases, the number of expected fatigue-involved crashes decreases. For the crash severity model, a positive coefficient implies that as the value of the variable increases, the likelihood of a more severe crash increases. A negative coefficient implies the opposite; as the value of the variable increases, the likelihood of a more severe crash decreases.

6.1 FARS Crash Frequency Model Discussion

Four independent variables were included in the final FARS crash frequency model specification. A discussion on how each independent variable impacts fatigue-involved crash frequency follows.

6.1.1 V9Sum

V9Sum represents the nine-year sum (2002 to 2010) of vehicle miles traveled for a specific state. The estimated coefficient for this variable is $0.788515\text{x}10^{-6}$ which was statistically significant at the 95% level (p-value = 0.0000 < 0.05). The vehicle miles traveled sum is a large number so a small coefficient was expected. For each extra mile traveled, the increased likelihood of a fatigue-involved fatal crash is $0.788515\text{x}10^{-6}$. The positive sign of the coefficient is intuitive as more vehicle miles traveled implies more exposure and a greater possibility of crashes.

6.1.2 Train

Train is a variable which describes whether or not officers of a state patrol agency receive formal training related to fatigue identification. This variable takes a value of one if officers receive training, zero if they do not, and was skipped in the model if a respondent did not answer the question. The estimated coefficient in the model was -0.86683568 and statistically significant at the 95% level (p-value = 0.0003 < 0.05).

The negative sign implies fewer fatigue-involved fatal crashes in a state where officers received formal training related to fatigue identification. The marginal effect of Train is -236.819508. This implies a state with fatigued driving training tended to have approximately 237 fewer fatigue-involved fatal crashes over the nine-year period.

6.1.3 PSA

The variable, PSA, describes whether or not a state patrol agency used public service announcements and driver education in their programs related to fatigued driving. The use of public service announcements and driver education programs was a common, qualitative response to Question 6 in the survey. This variable takes a value of one if a respondent mentioned these programs and zero if the respondent did not mention these programs. The estimated coefficient in the model was -0.23849687 but this estimate was not statistically significant at the 95% level (p-value = 0.2440 > 0.05). However, the variable was retained in the model as it retained a relatively high significance level regardless of the addition of other variables. Also, it was a commonly used technique by enforcement agencies so it provides some information as to its effectiveness even with the lower significance level. The negative sign implies a reduction in the expected number of fatigue-involved fatal crashes in a state with such programs. The marginal effect of -65.1573437 implies states which utilize public service announcements and driver education programs tended to have approximately 65 fewer fatigue-involved fatal crashes from 2002 to 2010.

While public service announcements and driver education may be effective means for improving safety, the data analysis failed to show strong statistical evidence in this regard. PSA was statistically significant at a 75% confidence level. It is possible there is some variable interaction between PSA and Train. Of the eight states which responded that they use public service announcements and driver education programs, six also responded they have fatigued driving training programs. This may be having an impact on the model but the actual effect is unknown.

6.1.4 Driving

Driving is a variable related to the qualitative answers to Question 9, the procedure for stopping a vehicle with a driver believed to be fatigued. Driving takes a value of one if the respondent mentioned driver cues are used to determine if a driver is fatigued during a stop. If this was not mentioned, Driving was assigned a value of zero.

The estimated coefficient in the model was -0.65548262 and statistically significant at the 95% level (p-value = 0.0473 < 0.05). The negative sign implies the expected number of fatigue-involved fatal crashes reduced in a state where patrol officers used driving cues to determine if drivers were fatigued. The marginal effect, -179.077853, implies states which use driving cues tended to have approximately 179 fewer fatigue-involved fatal crashes over the nine year period. Checking driving cues appears to improve safety, possibly because more officers will correctly identify fatigue and remove impaired drivers from the roadway. Driving cues have a smaller impact on safety than fatigued driving training programs and a greater impact than public service announcements and driver education programs. This is exemplified by the magnitude of the estimated coefficient.

6.2 HSIS Crash Frequency Model Discussion

Three variables were included in the final HSIS crash frequency model. The following sections discuss each variable individually.

6.2.1 VMT

VMT represents the total number of vehicle miles traveled in a state for a specific year of data. The year depends on what was available from the HSIS database. The estimated coefficient for VMT is 0.660541×10^{-5}. The positive sign implies more vehicle miles traveled leads to more crashes. This is reasonable as more vehicle miles traveled implies a greater exposure and more chances for crashes to occur. VMT is a relatively large number so a small coefficient was expected. One extra mile of driving in a state is unlikely to have a noticeable impact on crashes and a large increase in VMT is necessary for a noticeable effect. VMT was statistically significant at a 95% level (p-value = 0.0000 < 0.05).

6.2.2 SpecProg

SpecProg is a variable related to the answer to Question 6 in the telephone survey. It describes whether or not a state has a specific program dealing with fatigued driving. This variable was coded as one if the respondent answered “yes” and zero if they responded “no”. The variable was coded as a missing value and skipped in the model if respondent did not know. This was not an issue in the HSIS model as all states included answered Question 6. The marginal effect for SpecProg is -169.995476. This implies states with fatigued driving programs tended to have approximately 170 fewer fatigue-involved crashes in a given year. SpecProg is statistically significant at a 95% confidence level (p-value = 0.0276 < 0.05).The negative sign implies a state had fewer fatigue-involved crashes if they had a specific program related to fatigued driving. Model results show that fatigued driving programs have a positive effect on safety.

6.2.3 DriverIn

The variable, DriverIn, refers to a qualitative response to Question 9 of the telephone survey. This question asked about an agency’s procedure when stopping a driver believed to be fatigued. DriverIn takes a value of one if a respondent mentioned a driver interview was part of a stopped vehicle procedure and zero if they did not. The estimated coefficient for DriverIn is -0.13161595. The negative sign implies states which include a driver interview in their stopped vehicle procedures tend to have fewer fatigue-involved fatal crashes. A marginal effect of -113.033851 implies states which interview stopped drivers tended to have approximately 113 fewer fatigue-involved crashes in a given year.

Driver interviews may be an effective way to identify fatigued drivers. DriverIn is statistically significant at an 80% confidence level (p-value = 0.1607 > 0.05). It was retained in the model as it was a common technique used by law enforcement officials and its addition improved the McFadden pseudo r-squared of the model.

6.3 Crash Severity Model Discussion

The crash severity model takes a different form than the previously discussed crash frequency models. Instead of estimating the number of crashes, the model estimates thresholds which separate crashes of different severity levels. The variables discussed earlier all represented some increase or decrease in number of crashes where the magnitude of the variable is the amount by which the number of crashes is changed. In the crash severity model, the magnitude is not as directly linked. Each variable's magnitude should be considered relative to the others to understand which are having a greater impact on severity. Four variables were statistically significant in the estimated crash severity model; each variable is discussed individually in the next section.

6.3.1 Driving

Driving is a variable which represents a qualitative response to Question 9 of the telephone survey. It was given the value of one if the respondent mentioned driving cues as part of their stopped vehicle procedure and zero if they did not. The estimated coefficient for Driving is -0.17643818 which implies crashes tend to be less severe if enforcement officers look for driving cues to identify fatigue. The variable was statistically significant at a 95% confidence level (p-value = 0.0000 < 0.05).

6.3.2 Winter

The variable, Winter, is an indicator variable describing whether or not a specific crash occurred in the winter. If a crash occurred in December, January, or February this variable was given a value of one and zero if it occurred in other months of the year. The coefficient for Winter was estimated as -0.07060437 and was statistically significant at a 95% confidence level (p-value = 0.0006 < 0.05). The negative coefficient implied that crashes in winter tended to be less severe than those in other seasons.

6.3.3 Func1

The variable, Func1, was created with information from the HSIS database. It is an indicator for a specific roadway functional class. Func1 takes the value one if the roadway segment where a crash occurred is a principle arterial and zero if it occurred on a segment of a different class. This information was not included for some crashes and was considered a missing value.

The coefficient for Func1 was estimated to be 0.04981127 and statistically significant at a 95% confidence level (p-value = 0.0134 < 0.05). The positive coefficient implies crashes on principle arterials are more severe than those which occur on other functional classes. This may be caused by the fact that principle arterials generally have many obstructions on the side of the roadway and may not have separated opposing traffic flows. A fatigued driver may drift into a head on collision or strike an obstruction on the roadside. These are often severe crashes. The coefficient for Func1 is small; it has a smaller effect on severity than either Driving or Winter.

6.3.4 Stop

Stop is a variable which describes a respondent's answer to Question 8 of the telephone survey. This question asks if an organization's officers stop vehicles if they believe the drivers are fatigued. It is given a value of one if they do, zero if they do not, and considered a missing value if the respondent said they did not know.

The estimated coefficient for Stop is -0.02493353. The negative sign implies crashes in states where enforcement officers stop vehicles if they believe drivers are fatigued tend to be less severe than in other states. The magnitude of the coefficient is the smallest of any included in the model showing it has the least effect. Stop is statistically significant at a 75% confidence level (p-value = 0.2366 > 0.05). Stop was retained in the model as it improved the McFadden pseudo r-squared value of the model. Also, it maintained a relatively high significance level with the addition of other variables.

7.0 CRITICAL VARIABLES

An enforcement technique which has a positive effect on safety should either reduce the number of crashes or the severity of crashes. Of the variables considered in the three models, only Driving was statistically significant in two models. This variable was found to reduce both the number of fatigue-involved fatal crashes and the severity of fatigue-involved crashes. As it was significant in two models, it has the most evidence of being an effective enforcement technique of any considered in the models.

It is possible other variables would show a similar result if the information used to estimate the models was more complete. Some variables which gave positive results in the FARS crash severity model could not be used in the other two models. This was caused by the fact that the HSIS data covered only five states. The small sample size meant some variables were collinear and could not be used in the model. The variable, Train, was statistically significant in the FARS crash frequency model but could not be tested in either HSIS model as all states had the same value for this variable. It is possible Train has a similar positive effect in both situations similar to Driving but could not be shown with the available data. Its effect on crash severity was not tested.

8.0 MODEL LIMITATIONS

While the three statistical models showed evidence of some fatigued driving enforcement techniques improving safety, it is important to understand potential shortcomings of this research. These shortcomings may stem from three specific sources: survey responses, crash cause characterization, and sample size. A discussion of each cause follows.

8.1 Survey Responses

The independent variables used in all three crash models primarily came from responses to the telephone survey administered to state patrol agencies. Error may have been introduced in the crash models due to incorrect or incomplete answers to the survey questions. Contact information for each state patrol agency was found on its respective website. Each agency is organized differently so it was difficult to find respondents who held similar positions. Some respondents referred the surveyor to another person at the agency, but some were still unable to answer the questions. It is possible some respondents answered to the best of their knowledge but were unaware of all programs and policies at the agency and provided incorrect or incomplete information.

Indicator variables were created to utilize qualitative responses to the survey questions in the crash models. These variables were created to improve the models but they may not be completely accurate. Many qualitative responses were offered in response to “yes” or “no” questions without surveyors soliciting further explanation. It is possible some respondents were more likely to expound upon their answers than others. If this is the case, it is likely the techniques described by the indicator variables are being used by more states than the survey shows. There may be error in these variables because of variation in how the survey was approached. These errors would affect the crash models and it is unknown what impact the survey responses had.

In addition to these potential errors introduced by the survey process, the survey did not retrieve as much information as possible. A common response about the procedure during a traffic stop was a driver interview. Many respondents did not explain further and describe what to look for in a driver interview. One objective of the survey was to investigate enforcement techniques for further research. Without any specifics, these responses do not meet this objective and do not provide a technique to research in the future.

8.2 Crash Cause Characterization

Error likely entered into the statistical modeling process due to how crash cause is characterized. Both the FARS and HSIS databases provide a cause for every crash listed in the database. This cause comes from police reports. Only data related to crashes caused by fatigue were used in the models. As shown by the literature review and telephone survey results, there is evident subjectivity in determining a crash cause and no current, effective way to identify fatigue. If fatigue cannot be correctly identified as the cause of a crash, there are likely significant errors in the crash databases. The crash models will not be accurate if the data is inherently flawed. Until a better method of identifying fatigue is found, there is no accurate information available as all databases fall victim to the same issues of crash cause characterization.

8.3 Commercial and Non-Commercial Drivers

Error may have been introduced to the model due to inconsistent data sources. The survey requested information related to enforcement techniques. Fatigued driving is only regulated in the case of commercial drivers so the retrieved information is relevant to commercial drivers. The FARS and HSIS databases provide crash data for all fatigue-involved crashes. This includes crashes for non-commercial drivers. Similarly, the vehicle miles traveled data include all drivers. There is not enough detail of these data sources to separate crashes which include commercial drivers. The models would likely be somewhat different if only data relevant to commercial drivers was used. The models would be better able to identify the true effects of enforcement.

8.4 Sample

All three crash models are limited by the available sample size of data. In the case of the fatal crash frequency model, there are only 49 data points (one for each state). This was unavoidable with the use of telephone survey results as independent variables. Ideally, any crash frequency model would have a larger sample size. Within the data points, the number of crashes was also small. Over the nine years of data retrieved, states had anywhere between 29 and 2865 fatigue-involved fatal crashes. This small number of crashes may have negatively affected the accuracy of the crash models. With only three crashes occurring in some states in a year, it is difficult to recognize the effects of enforcement techniques. The small number of fatigue-involved fatal crashes in the FARS database meant the data were aggregated over time. Detail is lost when data is aggregated. The models may have produced different results if each year was considered an individual observation.

In the case of the crash severity model created using the HSIS data, the sample size appears to be greater than it truly is. While thousands of crashes were retrieved from the database, information was only used from five different states. The survey responses which created the majority of the independent variables were state specific. All crashes which occurred in a specific state had very similar values for the independent variables in both models. This lack of variability may have affected the model outputs. As discussed previously, some variables had to be excluded from these models as they were collinear across the five states. This limited the accuracy of the models and the potential information which could be gleaned from them.

The small number of states introduces another limitation. Each year is treated as a different observation but this means observations' independent variables are similar. State-specific observations shared common characteristics across years; the telephone survey results remained the same for each year. Observations should be independent but are not. Observation independence is a primary assumption of statistical models and introduces bias into the results.

9.0 CONCLUSIONS

The literature review, telephone survey, and statistical models yielded a variety of information related to fatigued driving identification and enforcement techniques. Some techniques show promise for use by law enforcement officers while the analysis did not uncover evidence regarding the effectiveness of others in improving safety related to fatigued driving. Fatigue identification remains an issue and in view of significant differences in the rates of fatigue identification as the cause of crashes amongst states, the results from the statistical models may be victims of data bias. If fatigue cannot be correctly identified as the cause of a crash, the crash databases used to estimate the models are limited. The next sections detail the conclusions from the literature review, telephone survey, and statistical models.

9.1 Literature Review Conclusions

The literature review studied the issue of how to categorize fatigue as there is a wide range from being awake to being asleep. Current regulations do not well define the level at which fatigue is considered an impairment. One study discussed in the literature review used mental calculations to delineate an unacceptable level of fatigue. This method would be easy to implement in a traffic stop if law enforcement officers are given an objective, repeatable test. Other methods used in studies discussed in the literature review would be more difficult to implement. Some studies used trained observers, but without more information on how they were trained it would be difficult to get all enforcement officers to a level of expertise to identify fatigue without specific indicators.

The literature review identified several potential methods for recognizing fatigue in drivers. Some of these methods may be effective while others may not. Based on previous research, respiration, eye closure, and driving cues may be potentially used by law enforcement officers to recognize fatigued drivers. Each of these methods may be easily observed in a traffic stop. Other methods, while effective for identifying fatigue, may not be as easily used by enforcement officers. For example, heart rate, EEG readings, and skin conduction are not easily observed in a traffic stop. Issues arise because many of these characteristics such as heart rate and breathing patterns may be affected by the stress of a traffic stop. Also, some people naturally have different breathing patterns or varying levels of eyelid drooping so officers may have trouble identifying baselines with which to compare stopped drivers. Privacy issues may be another hurdle in implementing techniques relying on relatively invasive procedures such as heart rate monitoring, EEG, and skin conduction tests.

9.2 Telephone Survey Conclusions

The telephone survey made it apparent many states do not have specific policies and procedures related to fatigued driving beyond those stipulated by the federal government. Most states' respondents said they have fatigued driving policies and training programs. Seven states mentioned state-specific programs for fatigued driving but did not include any details related to the program. If further information on these programs is desired, these states would need to be contacted again.

The telephone survey results provided evidence that current fatigued driving regulations and identification techniques are insufficient. Five states said fatigue is only declared to be the cause of a crash if there was a "driver admission" when interviewed. One agency stated there is "no way" to determine fatigue to be the cause of the crash. Enforcement agencies require more guidance on identifying fatigued driving and many states only include federal regulations in their training programs. Crash data related to fatigued driving is likely biased due to reporting. Databases rely on police reports to determine crash cause. Until law enforcement officers can correctly identify the cause, any research done related to fatigued driving will have limitations.

9.3 Crash Model Conclusions

The three crash models estimated using information from the telephone survey provided some evidence as to successful fatigued driving enforcement techniques. Six fatigued driving enforcement techniques were shown to have a positive effect on safety by either reducing the number of crashes or reducing the severity of fatigue-involved crashes. States that trained state patrol officers about fatigued driving tended to be safer than those that did not provide such training. Additionally, two techniques were related to a state patrol's agency policy on fatigued driving enforcement. These techniques were public service announcements and driver education programs and any state's specific program related to fatigued driving. Safety appears to be improved in states which have fatigued driving programs and in those which use public service announcements and driver education programs.

Some enforcement techniques used by law enforcement officers in a traffic stop were shown to improve safety in the crash models. States tend to be safer when their officers stop vehicles if they feel their drivers are fatigued and if their officers interview drivers during a traffic stop. One enforcement technique for use by state patrol officers was shown to both reduce the number of fatigue-involved crashes and reduce the severity of crashes caused by fatigue. This technique is the use of driving cues to determine if a driver is fatigued. This technique was shown to have the greatest potential to improve safety of any found in the telephone survey.

While some techniques found in the telephone survey were not well explained, there is evidence to show some states' policies improve safety. Officer training, state-specific programs, and good procedures during a traffic stop for identifying driver fatigue were all shown to have positive effects on safety in the crash models. The models have shown driving cues to the most effective technique for improving safety. Some of these techniques were the most commonly mentioned techniques mentioned in the telephone survey.

10.0 FUTURE RESEARCH TOPICS

This thesis presented findings of some of the first research related to fatigued driving enforcement techniques. A telephone survey investigated techniques used by state patrol agencies across the country. While respondents gave some information about their states’ procedures and policies, responses were often vague. Crash models attempted to evidence correlations between these enforcement techniques and safety. The data available related to fatigue-involved crashes are likely biased so there is error in the models. It will be difficult to show any enforcement technique is having a noticeable effect on safety until reporting can be improved. Fatigue identification must be improved and techniques investigated by the literature review and telephone survey may be a good starting point to determine better techniques. Driving cues and driver interviews (especially eyelid droop and blinking characteristics) show promise for fatigue identification but require further research..

Future research should focus on methods for objectively identifying fatigue in drivers. As this research has focused on enforcement, special consideration is necessary to determine identification methods which could be used by enforcement officers. Previous research has not studied fatigue identification from this standpoint. Any fatigued driving enforcement technique to be studied must be shown to be objective, repeatable, scientifically sound, and able to hold up against a court challenge. It may be advantageous to include medical and legal personnel in future research to ensure this.

In addition to medical and legal personnel, it may also be beneficial to seek partnerships with commercial trucking companies and insurance companies. Commercial trucking companies already use technology to enforce proper driving habits. In-vehicle devices could be used to track drivers’ lane position and track their eye movements. If commercial trucking companies work to limit fatigued driving through their own technologies, it is likely to have a greater impact on safety than any enforcement technique. Also, insurance companies could be used to provide an incentive to companies which use technologies to combat fatigued driving. If insurance companies provided discounts to companies using effective technologies, they are more likely to be utilized. Having partners in the private sector could be very beneficial for safety as well as enforcement. Seeking and considering input from trucking companies may help avoid legal challenges from drivers for any new fatigued driving enforcement techniques.

The crash models suggest some enforcement techniques currently in use are positively affecting safety. Future research should study these techniques more closely to see if they have the potential for use as a nationwide procedure related to fatigued driving. Future research may also work to provide more complete guidance for fatigue identification. Driver interviews were shown to reduce the number of crashes caused by fatigue but little information was retrieved related to how to perform a driver interview. Future research could work to create more specific procedures to ensure these interviews are conducted by all officers in the same manner. More research is necessary to gain a thorough understanding of fatigued driving enforcement.

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APPENDIX A. TELEPHONE SURVEY

The University of Nebraska-Lincoln is conducting a survey in partnership with the Nebraska State Patrol to find out how different state enforcement agencies deal with the issue of fatigued motor vehicle driving. The questions merely pertain to policies and procedures for your state. The information will be used to help us design a more effective strategy to deal with the issue of driver fatigue. Are you the best person to answer a few questions in this context?

[If yes] This survey should take less than 15 minutes and I am grateful for your assistance.

[If not the correct person] Who would be the best person to speak with?

1. Responding Agency:

2. Agency contact information:

Address____

____

Phone:____________________Email:____________________

3. Respondent Name:

4. Respondent contact information (if different from above):

Address____

____

Phone:____________________Email:____________________

5. Does your agency have published rules and regulations dealing with the issue of fatigue in commercial motor vehicle drivers?

1 Yes
2 No
3 Don't know

If yes, can I access it online or receive it via email or postal mail?

6. Does your agency have any specific program that deals with the issue of fatigued motor vehicle drivers?

1 Yes
2 No
3 Don't know

If yes, can I access it online or receive it via email or postal mail?

7. Do officers in your agency receive formal training about identifying fatigue in motor vehicle drivers?

1 Yes
2 No
3 Don't know

If yes, can I access it online or receive it via email or postal mail?

8. Do officers in your agency stop vehicles if they believe drivers are fatigued?

1 Yes
2 No
3 Don't know

9. What procedure is followed when an officer stops a driver believed to be fatigued?

10. How is fatigue determined to be an issue in a motor vehicle crash?

The next section of the interview asks questions concerning available statistics about commercial vehicle inspections and citations. I realize that you may not have these statistics readily available, so please let me know where I may be able to access the statistics.

11. How many commercial motor vehicle inspections were carried out in the last year for which statistics are available?

Number of inspections: ___________

Year of inspections: ___________ (e.g., 2011)

If not known, is there a website or other place where I can find information on citations?

12. How many citations were issued by your agency for fatigued driving (both commercial and non-commercial drivers) in the last year for which statistics are available?

If not known, is there a website or other place where I can find information on citations?

13. Of these, how many citations were to commercial motor vehicle drivers?

If not known, is there a website or other place where I can find information on citations?

14. How many of these citations were challenged in the court?

If not known, is there a website or other place where I can find information on the court challenges?

15. Of those that were challenged, how many were successfully prosecuted?

If not known, is there a website or other place where I can find information on the successful prosecutions?

16. How many highway crashes were attributed to fatigue in the last year for which statistics are available?

Number of fatigue-involved crashes: ___________

Year of those crashes: ___________ (e.g., 2011)

If not known to the respondent, is there a website or other place where I can find information on crashes involving fatigue?

That is all the questions I have. Thank you again for your help. If you have any questions about the how this information will be used you can contact Dr. Aemal Khattak of the University of Nebraska-Lincoln at

402-472-8126 or if you think of any other information or resources that will help us understand how this is handled in your state, please feel free to email [BOSR email].

APPENDIX B. SAMPLE SAS CODE FOR MERGING FILES

```
libname data 'M:\';
proc import out= data.ca09road1 datafile= "M:\ca09road.xls" dbms=xls replace; run;
proc import out= data.ca09acc1 datafile= "M:\ca09acc.xls" dbms=xls replace; run;
proc sort data = data.ca09road1(keep = cntyrte begmp endmp func_cls
aadt trk2ax  trk3ax  trk4ax  trk5ax rodwycls) out = ca09road1;
by cntyrte begmp;
run;

proc sort data = data.ca09acc1(keep = acc_date accyr caseno numvehs
rodwycls severity cnty_rte milepost) out = ca09acc1;
by cnty_rte milepost;
run;

data data.ca09accbased (keep = rtlow rtmatch dropac cntyrte begmp endmp func_cls
aadt trk2ax  trk3ax  trk4ax  trk5ax severity rodwycls acc_date accyr caseno numvehs)

data.ca09roadbased (keep = rtlow rtmatch dropac acc_date accyr caseno numvehs
rodwycls severity cnty_rte milepost begmp endmp func_cls aadt trk2ax trk3ax trk4ax trk5ax);

link readlog;
link readacc;

loop:     if cntyrte = 'AAAAAAAAAA' then stop;

if cntyrte > cnty_rte then
do;
rtlow + 1;
link readacc;
go to loop;
end;

if cntyrte < cnty_rte then
do;
link roadout;
link readlog;
go to loop;
end;

* at this point there is a match on route. the next step is to
* compare milepost on accident file with begmp and endmp on
* roadlog rile.;
```

```
if (milepost >= begmp  or abs(milepost - begmp) < .005 )
and (milepost <= endmp  or abs(milepost - endmp) < .005)
then do;
rtmatch + 1;
link accout;
link readacc;
go to loop;
end;
else if milepost < begmp then
do;
dropac + 1;
link readacc;
go to loop;
end;
else if milepost > endmp then
do;
link roadout;
link readlog;
go to loop;
end;
return;

accout:

output data.ca09accbased;

return;

roadout:

output data.ca09roadbased;

return;

readlog:
if eoflog then do;
cntyrte = 'AAAAAAAAAA';
end;
else
do;
set ca09road1 end=eoflog;
end;
return;

readacc:
if eofacc then do;
```

```
cnty_rte = 'AAAAAAAAAA';
put dropac = 'missing sections';
put rtlow = 'accs on missing routes';
put rtmatch = 'accidents counted';
end;
else do;
set ca09acc1  end=eofacc;
end;
return;
run;
```

APPENDIX C. SAMPLE SAS CODE FOR LARGE ROAD FILES

```
libname data 'M:\';
proc import out= data.il06acc1 datafile= "M:\il06acc.xls" dbms=xls replace; run;
proc sort data = data.il06roadnew(keep = cntyrte begmp endmp
aadt func_cls rodwycls comm_vol) out = il06roadnew;
by cntyrte begmp;
run;

proc sort data = data.il06acc1(keep = acc_date accyr caseno numvehs
rodwycls severity cnty_rte milepost) out = il06acc1;
by cnty_rte milepost;
run;

data data.il06accbased (keep = rtlow rtmatch dropac cntyrte begmp endmp func_cls
aadt severity rodwycls acc_date accyr caseno numvehs comm_vol)

data.il06roadbased (keep = rtlow rtmatch dropac cnty_rte begmp endmp func_cls
aadt severity rodwycls acc_date accyr caseno numvehs comm_vol);

link readlog;
link readacc;

loop:   if cntyrte = 'AAAAAAAAAA' then stop;

if cntyrte > cnty_rte then
do;
rtlow + 1;
link readacc;
go to loop;
end;

if cntyrte < cnty_rte then
do;
link roadout;
link readlog;
go to loop;
end;

* at this point there is a match on route. the next step is to
* compare milepost on accident file with begmp and endmp on
* roadlog rile.;

if (milepost >= begmp  or abs(milepost - begmp) < .005 )
and (milepost <= endmp  or abs(milepost - endmp) < .005)
then do;
```

```
rtmatch + 1;
link accout;
link readacc;
go to loop;
end;
else if milepost < begmp then
do;
dropac + 1;
link readacc;
go to loop;
end;
else if milepost > endmp then
do;
link roadout;
link readlog;
go to loop;
end;
return;

accout:

output data.il06accbased;

return;

roadout:

output data.il06roadbased;

return;

readlog:
if eoflog then do;
cntyrte = 'AAAAAAAAAA';
end;
else
do;
set il06roadnew end=eoflog;
end;
return;

readacc:
if eofacc then do;
cnty_rte = 'AAAAAAAAAA';
put dropac = 'missing sections';
put rtlow = 'accs on missing routes';
```

```
put rtmatch = 'accidents counted';
end;
else do;
set il06acc1  end=eofacc;
end;
return;
run;
```

APPENDIX D. COMPLETE VARIABLE LISTING

Related Survey Question Number	Variable Name	Variable Description	Coding
5	PubReg	Published rules and regulations for fatigued commercial motor vehicle drivers	1=Yes 0=No -999=Don't Know
5	FedReg	Mentioned federal regulations	1=Yes 0=No
5	StateReg	Mentioned specific state regulations	1=Yes 0=No
6	SpecProg	Specific program dealing with fatigued driving	1=Yes 0=No -999=Don't Know
6	FedProg	Mentioned federal programs	1=Yes 0=No
6	PSA	Mentioned public service announcements and education	1=Yes 0=No
6	OtherProg	Mentioned some other program	1=Yes 0=No
7	Train	Officers receive formal fatigue identification training	1=Yes 0=No -999=Don't Know
7	FedTrain	Mentioned federal training programs	1=Yes 0=No
7	OtherTra	Mentioned some other training program	1=Yes 0=No
8	Stop	Officers stop vehicles if they believe drivers are fatigued	1=Yes 0=No -999=Don't Know
9	StopFed	Mention federal regulations as part of stopped vehicle procedure	1=Yes 0=No
9	StopLog	Mention checking log books as part of stopped vehicle procedure	1=Yes 0=No
9	DriverIn	Mentioned driver interview as part of stopped vehicle procedure	1=Yes 0=No
9	CMVOos	Mentioned taking fatigued CMV driver out of service as part of stopped vehicle procedure	1=Yes 0=No
9	Driving	Mentioned driving cues as part of stopped vehicle procedure	1=Yes 0=No

9	Impair	Mentioned checking for drug, alcohol, etc. impairment first in stopped vehicle procedure	1=Yes 0=No
9	TrafficViol	Mentioned citing other traffic violations in stopped vehicle procedure	1=Yes 0=No
9	Discret	Mentioned officer discretion as part of stopped vehicle procedure	1=Yes 0=No
10	CrshLog	Mentioned checking log books as part of fatigue determination in a crash	1=Yes 0=No
10	CrshChar	Mentioned checking crash characteristics as part of fatigue determination in a crash	1=Yes 0=No
10	DrverState	Mentioned taking driver and witness statements as part of fatigue determination in a crash	1=Yes 0=No
10	Observ	Mentioned officer observations as part of fatigue determination in a crash	1=Yes 0=No
10	Recon	Mentioned crash reconstruction as part of fatigue determination in a crash	1=Yes 0=No
11	Inspec	Number of commercial vehicle inspections in fiscal year 2011	Numerical value
11	LnInspec	Natural log of number of commercial vehicle inspections in fiscal year 2011	Numerical value
N/A	DOosR	Driver inspection out of service rate in fiscal year 2011	Numerical value
N/A	VoosR	Vehicle inspection out of service rate in fiscal year 2011	Numerical value
N/A	V9Sum	Sum of VMT (in millions) from 2002 to 2010	Numerical value
N/A	LnV9	Natural log of sum of VMT from 2002 to 2010	Numerical value
N/A	V5Sum	Sum of VMT (in millions) from 2006 to 2010	Numerical value
N/A	LnV5	Natural log of sum of VMT from 2006 to 2010	Numerical value
N/A	F9Sum	Sum of fatigue-involved fatal crashes from 2002 to 2010	Numerical value
N/A	F5Sum	Sum of fatigue-involved fatal crashes from 2006 to 2010	Numerical value
N/A	Aadt	Annual average daily traffic of roadway segment where crash occurred	Numerical value
N/A	Func1	Roadway segment where crash occurred is a principle arterial	1=Yes 0=No -999=Unknown functional class
N/A	Func2	Roadway segment where crash occurred is a minor arterial	1=Yes 0=No -999=Unknown functional class
N/A	Func3	Roadway segment where crash occurred is a major collector	1=Yes 0=No -999=Unknown functional class

N/A	Func4	Roadway segment where crash occurred is a minor collector	1=Yes 0=No -999=Unknown functional class
N/A	Func5	Roadway segment where crash occurred is a local road	1=Yes 0=No -999=Unknown functional class
N/A	Rodwy1	Roadway segment where crash occurred is an urban freeway with four or more lanes	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy2	Roadway segment where crash occurred is an urban freeway with less than four lanes	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy3	Roadway segment where crash occurred is an urban two lane road	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy4	Roadway segment where crash occurred is an urban multilane divided non-freeway	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy5	Roadway segment where crash occurred is an urban multilane undivided non-freeway	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy6	Roadway segment where crash occurred is a rural freeway with four or more lanes	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy7	Roadway segment where crash occurred is a rural freeway with less than four lanes	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy8	Roadway segment where crash occurred is a rural two lane road	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy9	Roadway segment where crash occurred is a rural multilane divided non-freeway	1=Yes 0=No -999=Unknown roadway class
N/A	Rodwy10	Roadway segment where crash occurred is a rural multilane undivided non-freeway	1=Yes 0=No -999=Unknown roadway class
N/A	Urban	Crash occurred in urban location	1=Yes 0=No -999=Unknown
N/A	Crshsev	Severity of crash	0=Property damage only 1=C-type injury 2=B-type injury 3=A-type injury 4=Fatal crash
N/A	Yr2006	Crash occurred in 2006	1=Yes 0=No

N/A	Yr2007	Crash occurred in 2007	1=Yes 0=No
N/A	Yr2008	Crash occurred in 2008	1=Yes 0=No
N/A	Yr2009	Crash occurred in 2009	1=Yes 0=No
N/A	Yr2010	Crash occurred in 2010	1=Yes 0=No
N/A	Yr2011	Crash occurred in 2011	1=Yes 0=No
N/A	Spring	Crash occurred in spring season	1=Yes 0=No
N/A	Summer	Crash occurred in summer season	1=Yes 0=No
N/A	Fall	Crash occurred in fall season	1=Yes 0=No
N/A	Winter	Crash occurred in winter season	1=Yes 0=No
N/A	Numvehs	Number of vehicles involved in crash	Numerical value

APPENDIX E. SOFTWARE OUTPUT FOR FARS CRASH FREQUENCY MODEL

```
+---------------------------------------------+
| Negative Binomial Regression                 |
| Maximum Likelihood Estimates                 |
| Model estimated: Nov 14, 2012 at 10:49:03AM.|
| Dependent variable                F9SUM      |
| Weighting variable                 None      |
| Number of observations               45      |
| Iterations completed                  1      |
| Log likelihood function       -278.6038      |
| Number of parameters                  6      |
| Info. Criterion: AIC =         12.64906      |
|   Finite Sample: AIC =         12.69818      |
| Info. Criterion: BIC =         12.88995      |
| Info. Criterion:HQIC =         12.73886      |
| Restricted log likelihood     -2169.709      |
| McFadden Pseudo R-squared      .8715940      |
| Chi squared                    3782.211      |
| Degrees of freedom                    1      |
| Prob[ChiSqd > value] =         .0000000      |
| NegBin form 2; Psi(i) = theta               |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------
+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of
X|
+--------+--------------+----------------+--------+--------+----------
+
 Constant|   5.70376888       .25256314    22.584   .0000
 V9SUM   |   .788515D-06    .157835D-06     4.996   .0000   557910.178
 TRAIN   |   -.86683568       .23937758    -3.621   .0003    .80000000
 PSA     |   -.23849687       .20471158    -1.165   .2440    .17777778
 DRIVING |   -.65548262       .33040337    -1.984   .0473    .11111111
---------+Dispersion parameter for count data model
 Alpha   |     .28414342       .06562979     4.329   .0000
```

APPENDIX F. SOFTWARE OUTPUT FOR HSIS CRASH FREQUENCY MODEL

```
+---------------------------------------------+
| Negative Binomial Regression                |
| Maximum Likelihood Estimates                |
| Model estimated: Mar 29, 2013 at 11:33:50AM.|
| Dependent variable              NUMCRSH     |
| Weighting variable                 None     |
| Number of observations               23     |
| Iterations completed                 12     |
| Log likelihood function       -132.0700     |
| Number of parameters                  5     |
| Info. Criterion: AIC =         11.91913     |
|   Finite Sample: AIC =         12.07258     |
| Info. Criterion: BIC =         12.16598     |
| Info. Criterion:HQIC =         11.98121     |
| Restricted log likelihood     -275.2891     |
| McFadden Pseudo R-squared      .5202498     |
| Chi squared                    286.4382     |
| Degrees of freedom                    1     |
| Prob[ChiSqd > value] =         .0000000     |
| NegBin form 2; Psi(i) = theta               |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|    5.76808582       .06424301    89.785   .0000
 VMT     |    .660541D-05    .431010D-06    15.325   .0000   131048.304
 SPECPROG|   -.19794173        .08987004    -2.203   .0276    .65217391
 DRIVERIN|   -.13161595        .09383369    -1.403   .1607    .34782609
---------+Dispersion parameter for count data model
 Alpha   |     .01274060       .00665528     1.914   .0556
```

APPENDIX G. SOFTWARE OUTPUT FOR CRASH SEVERITY MODEL

```
+---------------------------------------------+
| Ordered Probability Model                   |
| Maximum Likelihood Estimates                |
| Model estimated: Apr 01, 2013 at 02:34:30PM.|
| Dependent variable              CRSHSEV     |
| Weighting variable                 None     |
| Number of observations            19653     |
| Iterations completed                 12     |
| Log likelihood function       -22231.61     |
| Number of parameters                  8     |
| Info. Criterion: AIC =          2.26323     |
|   Finite Sample: AIC =          2.26323     |
| Info. Criterion: BIC =          2.26644     |
| Info. Criterion:HQIC =          2.26428     |
| Underlying probabilities based on Normal    |
+---------------------------------------------+

+---------------------------------------------+
| Ordered Probability Model                   |
| Cell frequencies for outcomes               |
|  Y Count Freq  Y Count Freq  Y Count Freq   |
|  0 11142 .566  1  3926 .199  2  3592 .182   |
|  3   783 .039  4   208 .010                 |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
---------+Index function for probability
 Constant|    -.15141842       .02109270    -7.179   .0000
 DRIVING |    -.17643818       .02677107    -6.591   .0000    .17045744
 WINTER  |    -.07060437       .02054105    -3.437   .0006    .20556658
 FUNC1   |     .04981127       .02014365     2.473   .0134    .31735613
 STOP    |    -.02493353       .02106865    -1.183   .2366    .42945097
---------+Threshold parameters for index
 Mu(1)   |     .56107950       .00783039    71.654   .0000
 Mu(2)   |    1.47287665       .01454027   101.296   .0000
 Mu(3)   |    2.13850454       .02597487    82.330   .0000

+-----------------------------------------------------------------------+
|   Cross tabulation of predictions. Row is actual, column is predicted. |
|   Model = Probit    .  Prediction is number of the most probable cell. |
+-------+-------+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| Actual|Row Sum|  0  |  1  |  2  |  3  |  4  |  5  |  6  |  7  |  8  |  9  |
+-------+-------+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|      0|  11139|11139|    0|    0|    0|    0|
|      1|   3923| 3923|    0|    0|    0|    0|
|      2|   3592| 3592|    0|    0|    0|    0|
|      3|    783|  783|    0|    0|    0|    0|
|      4|    208|  208|    0|    0|    0|    0|
+-------+-------+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|Col Sum|  19645|19645|    0|    0|    0|    0|    0|    0|    0|    0|    0|
+-------+-------+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
```