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Data and methods for studying commercial motor vehicle driver fatigue, highway safety and long-term driver health[☆]

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ABSTRACT

This article summarizes the recommendations on data and methodology issues for studying commercial motor vehicle driver fatigue of a National Academies of Sciences, Engineering, and Medicine study. A framework is provided that identifies the various factors affecting driver fatigue and relating driver fatigue to crash risk and long-term driver health. The relevant factors include characteristics of the driver, vehicle, carrier and environment. Limitations of existing data are considered and potential sources of additional data described. Statistical methods that can be used to improve understanding of the relevant relationships from observational data are also described. The recommendations for enhanced data collection and the use of modern statistical methods for causal inference have the potential to enhance our understanding of the relationship of fatigue to highway safety and to long-term driver health.

1. Introduction

Driver fatigue is known to be an important factor in vehicle crash risk. This is true for both passenger vehicles and commercial vehicles. The U.S. Department of Transportation's Federal Motor Carrier Safety Administration (FMCSA) and National Highway Traffic Safety Administration (NHTSA) Large Truck Crash Causation Study (LTCCS) in

2001–2003 found fatigue to be an associated factor in 13% of fatal and injury crashes involving at least one large truck (FMCSA, 2005). At the request of the FMCSA, the National Academies of Sciences, Engineering, and Medicine (NASEM) convened the Panel on Research Methodologies and Statistical Approaches to Understanding Driver Fatigue Factors in Motor Carrier Safety and Driver Health to assess the key factors leading to fatigue experienced by truck and bus drivers

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while driving and the implications for road safety. The Panel was also asked to assess the relationship of these factors to long-term driver health. Finally, the Panel was asked to identify potential improvements in data and research methods that could increase understanding of these issues. This article summarizes some of the main findings and recommendations of the Panel’s report (NASEM, 2016) with a focus on data issues and statistical methodology. The authors were panelists, NASEM staff, and consultants who served on the panel.

The term fatigue conventionally denotes a subjective sense of tiredness. In a scientific sense, the term fatigue refers to objective performance degradation due to inadequate sleep, physical exertion, extended time-on-task, and other factors. The review paper by Williamson et al. (2011) describes the link between various factors and performance decrements among commercial motor vehicle (CMV) drivers. Sleep disorders, such as obstructive sleep apnea (OSA), are one factor associated with increased fatigue and OSA is common in CMV drivers (Howard et al., 2004; Stoohs et al., 1995). In addition to potential impacts on CMV safety, insufficient sleep (from any cause) is a known risk factor for a wide range of health problems including hypertension, diabetes, obesity, depression, and cardio-vascular disease (Watson et al., 2015). These health problems can affect driver alertness and safety. They also have a significant impact on quality and length of life.

FMCSA is charged with monitoring and improving the safety of commercial motor vehicles. FMCSA addresses its mandate to improve CMV safety through educational programs, regulations, monitoring carrier performance, and enforcing compliance with safety and other regulations. The primary regulations through which FMCSA attempts to reduce driver fatigue are hours of service regulations, which limit driving and work hours, and a required medical examination. The hours of service regulations restrict hours of driving and on duty per work day and per work week. The medical examination, required at least every two years, is intended to identify any limitations for safe driving posed by driver health. Among other health factors, medical examiners check for hypertension, diabetes, and cardio-vascular disease. Examiners also ask about sleep problems but partially due to there being no specific guidance from FMCSA on this topic, there are limitations as to what can be ascertained as to which drivers are currently having interrupted sleep due to OSA.

FMCSA hours of service and medical exam regulations cannot address the myriad work-related and non-work-related factors that can influence fatigue (e.g., stress in different driving environments; time spent loading and unloading; insufficient sleep while off-duty; life stressors; fitness; etc.).

To provide accurate information about the causes of fatigue, its impact on driving and driver health, and ways to reduce its occurrence, FMCSA partnered with several Canadian organizations to create the web-based North American Fatigue Management Program (NAFMP). NAFMP provides modules relevant to drivers and other interested parties (e.g., motor carrier management, driver families).

The NASEM panel included a broad range of experts covering transportation, sleep and fatigue, occupational medicine, human factors, and statistics. In its report, the Panel provided a set of recommendations regarding data and statistical methodology to advance the community’s knowledge about the factors influencing crash risk and about the long-term health consequences of fatigue. The remainder of this paper is organized as follows. Section 2 describes a multi-factor framework that is helpful for understanding the complexity of assessing the impacts of fatigue. Section 3 focuses on the factors associated with fatigue and their impact on CMV safety. The emphasis is on recommendations for improving available data and for improving the statistical methods applied to this issue. Section 4 considers long-term driver health effects and data that would be necessary to better understand the impact of fatigue and other risk factors on driver health. Section 5 discusses the role of educational programs and new technology that may potentially enhance the ability to prevent, detect, and mitigate fatigue, and offers advice on how to ensure that they are used to maximum benefit. Section 6 provides a closing summary and discussion.

2. Framework

A challenge in assessing the relationship between driver fatigue, hours of service regulations, and CMV safety (and long-term driver health) is that there are a large number of interacting factors associated with crash risk that go well beyond driver fatigue. Partially due to this complexity, different studies have found different impacts even when studying the same risk factors. For example Jovanis et al. (2011) found length of driving time to be a significant predictor of crash risk for less-than-truckload carriers. On the other hand, Hanowski et al. (2008) found a visible spike in crash risk during the first hour of driving but no consistent evidence of a time-on-task effect. The differences in these and other results are likely due to incomplete handling of various confounding factors. To address this, a comprehensive multivariate approach is required to provide more convincing estimates of the impact of factors associated with crash risk. Table 1 provides a framework developed in NASEM (2016) for

Table 1
Selected Factors Associated With Crash Risk.

Predictor domain	Sample predictors	Possible data sources	Outcome variables
Driver	<ul style="list-style-type: none"> ● Demographics ● Health history ● Sleep history ● Hours driving; hours on the job ● Medications ● Experience ● Safety Record 	<ul style="list-style-type: none"> ● Bureau of Labor Statistics; ● Driver surveys 	<ul style="list-style-type: none"> ● Crash rate ● Serious crash rate ● Fatal crash rate ● Safety critical event rate ● Fatigue
Vehicle	<ul style="list-style-type: none"> ● Type of truck/bus ● Maintenance history ● Crash history ● Technology installed 	<ul style="list-style-type: none"> ● Carriers 	
Carrier	<ul style="list-style-type: none"> ● Fleet size ● Turnover rate ● Compensation method ● Safety culture ● Safety record 	<ul style="list-style-type: none"> ● US DOT ● Carriers 	
Environment	<ul style="list-style-type: none"> ● Weather ● Precipitation ● Traffic density ● Road type ● Safety features 	<ul style="list-style-type: none"> ● Police accident reports 	

Table 2
Recommendations Regarding Data Collection.

- There should be regularly scheduled surveys (every 5 to 10 years) to understand demographics and employment circumstances of all CMV drivers in various industry segments.
- Records from electronic on-board recorders could offer substantial research benefits. (This is currently prohibited by law.)
- Data from electronic data recorders on trucks and buses involved in serious crashes can provide relevant data that would be valuable to investigators and safety researchers.
- Those that capture driver performance data (e.g., large carriers, firms collecting telematics data, insurance companies) should be incentivized to increase the availability of such data for research on fatigue and highway safety.
- Baseline data on driving exposure is critical. It is required for different driving environments (types of roads) and at low levels of geographic aggregation
- Ongoing collection of objective and subjective data (longitudinal or repeated cross-sectional studies) from CMV drivers is critical to track changes in fatigue and alertness and in health status and the factors associated with such changes.

conceptualizing the factors associated with crash risk; the table helps illuminate data gaps and research needs. The table lists characteristics of the driver, the vehicle, the carrier, and the environment that are relevant to crash risk. Driver factors can include demographic information, health status, driving history, sleep history and sleep opportunities, hours driving and hours on the job, medications, experience, and safety record. The age and maintenance history of the vehicles are important as is the quality of the tires and brakes, and the technology with which the vehicle is equipped (e.g., forward collision warning systems, autonomous emergency braking). Carrier characteristics such as safety record and driver turnover can be informative as can carrier policies regarding driver compensation and safety culture. As an example, driver compensation can influence a driver's decision to pull over or keep driving: Paying drivers by the mile incentivizes them to accumulate more miles. Finally, characteristics of the driving environment including weather, precipitation, traffic density, road design, and safety features (e.g., rumble strips on the side of the road) can be crucial factors in crash risk. In assessing relationships between fatigue and long-term driver health, a similar framework is relevant although it would include only driver and carrier characteristics.

3. CMV safety

3.1. Data issues

Table 1 illustrates the broad range of factors, beyond time-on-task or hours of service, that affect crash risk. Isolating the effect of hours of service, or any other factor addressed by FMCSA regulations therefore requires a wide range of data to control for potentially confounding factors. The panel report reviews available data sets and makes a number of recommendations regarding the collection and sharing of data; these are discussed below and summarized in Table 2.

Existing data include the NHTSA Fatal Analysis Reporting System (FARS) which provides a census file of motor vehicles (passenger and commercial) involved in traffic crashes with at least one fatality. The data are gathered by analysts in each state using police accident reports, hospital reports, and information from other relevant sources. Separate censuses of trucks and buses involved in fatal accidents (TIFA = Trucks Involved in Fatal Accidents, BIFA = Buses Involved in Fatal Accidents) were collected by the University of Michigan Transportation Research Institute with support from FMCSA. The TIFA and BIFA files include data from the FARS file along with additional data collected by researchers. Both TIFA and BIFA were discontinued after 2010. The National Automotive Sampling System (NASS) General Estimates System (GES) database compiled by NHTSA is a large statistical sample (approximately 50,000 police accident reports per year) of crashes with property damage, injury, or death. The data are collected from police accident reports. FMCSA maintains the Motor Carrier Management

Information System (MCMIS) crash file, a census of all trucks and buses involved in a crash that results in a fatality, an injury requiring transportation for immediate care, or a vehicle towed due to disabling damage. FMCSA uses the MCMIS crash and inspection files, along with the MCMIS carrier file, to identify unsafe carriers and take enforcement actions.

A key challenge of studying crash risk related to fatigue is that all crash data ultimately trace back to police crash reports, and the identification of fatigue on police reports is likely underreported. There is currently no objective test, such as a specific, sensitive biomarker, for fatigue that is available to police at crash scenes, as there is for alcohol. Reporting officers therefore have to rely on driver and witness statements along with their own judgment. Studies of fatigue require the kind of careful and broad-ranging data collection that was done in the LTCCS study described at the start of this article. In addition, assessing the risk of fatigue from observed crash data is challenging without matching exposure data. For example, if more crashes are found to occur in the afternoon than in the morning but the volume of trucks on the road is much higher in the afternoon then the risk per mile driven might actually be lower in the afternoon than it appears just from the raw crash counts. Accordingly, exposure data has also been identified as a critical need in assessing carrier safety (NASEM, 2017).

Other approaches that are used to assess the effect of fatigue on crash risk rely on naturalistic driving data or simulator studies. Naturalistic driving studies collect data on driver behavior in the normal operating environment using trucks equipped with video cameras and other sensors. Data are collected continuously while the truck is driven and can include video of the driver, traffic in front of and beyond the vehicle, and various measurements of truck motion and position. This typically creates an enormous data set. Analyses generally focus on short time intervals before and after certain triggered events (sometimes called safety critical events) like sudden braking, drifting out of lane, or a crash of some sort. Naturalistic driving studies are useful in that they gather indicators or measures of actual driving behavior. Also, because data are collected continuously it is possible to identify “control” segments with which to compare the various triggered events. Limitations include the need for further study to establish the relationship between safety critical events and crashes to determine which events are predictive of crashes. For example, crashes frequently occur when drivers fail to brake when they should; thus it is not clear if data collected because of a sudden braking event (which may be an appropriate avoidance maneuver) sheds light on braking-related crashes. Also, since naturalistic driving data often includes intrusive aspects like recording the driver himself, the set of drivers willing to participate may not be representative of the broader population.

In contrast with naturalistic driving studies, simulator studies assess drivers in a controlled, simulated environment. Although this leads to concerns about generalizability to the unconstrained real world, simulator studies allow for specific investigation of the effects of fatigue, drugs, or alcohol that cannot be ethically collected with drivers in real traffic.

Additional data relevant to the effects of fatigue may exist in other sources such as driver logs, roadside vehicle/driver inspection reports, records of large truck carriers, and data collected by private research organizations (e.g., the American Transportation Research Institute). New technology such as electronic logging devices, on-board safety systems (electronic stability control, lane departure warning, forward collision warning, etc.) and telematics used for locating and tracking vehicles also have the potential to assist researchers by providing data on hours driven, miles driven, decrements in vehicle control, and other data relevant to exposure and driver performance. However, it should be noted that the problem of directly and objectively identifying fatigue remains.

3.2. Statistical methods

The key question in much research on driver fatigue is the degree to which fatigue is a causal factor for highway crashes. Assessing whether fatigue is a cause in a particular incident is challenging for several reasons. First, there is no reliable way after a crash to tell whether fatigue played a critical role. Frequently fatigue determinations are made by a police officer at the scene primarily to ensure victims and the public are safe. Second, crashes often result from a combination of factors including driver condition, actions of other drivers, roadway and weather conditions, etc. If a runoff crash occurs involving a drowsy driver on a curved road segment with light precipitation, then it is not really possible to identify the contribution of any one factor.

Indeed, the statistical literature distinguishes between the *effects of causes* (what would be the effect if a particular cause or intervention occurred, i.e., a particular change was made such as a change in the lighting on a road segment or a change in the law about legal blood alcohol levels) and the *causes of effects* (what caused the particular observed effect, i.e., what caused the above mentioned crash involving the drowsy driver in light precipitation) (see, e.g., Dawid et al., 2014). It is generally noted in that literature how difficult it is to determine the causes of effects. Instead, statistical research frequently focuses on assessing the causal effect of a particular exposure or treatment of interest with all other factors held constant (i.e., the effect of one cause in comparison to another) (Holland, 1986).

Randomized clinical trials are often used in medical contexts to estimate causal effects. In such trials a sample of individuals with a given condition are randomly assigned to one of two or more different treatments. The random assignment ensures that the treatment groups should be similar with respect to all other factors that might also affect the outcome. In the context of fatigue, randomized studies are possible in the laboratory (e.g., in a simulator study) but such studies do not necessarily generalize to real world situations.

An alternative to randomized controlled trials (RCT) that is often more feasible is referred to as randomized encouragement designs, which retain many of the benefits of RCT trials (West et al., 2008). In randomized encouragement designs, subjects are not randomized to the treatment of interest (e.g., using a continuous positive airway pressure (CPAP) machine to address OSA), but rather to some “encouragement” to use the treatment (e.g., a coupon for a substantially reduced price on a CPAP machine). These designs allow the estimation of the effect of the encouragement (using standard RCT methods), as well as the effect of actually taking the treatment of real interest (using instrumental variables estimation approaches).

For the most part, though, insights into driver fatigue rely on observational studies where researchers do not assign the treatment of interest (e.g., a particular work-rest schedule). As noted above, the key difficulty with observational studies is there are generally many other potentially confounding factors (e.g., those identified in Table 1) that may differ between the groups being compared. In such cases it is critical to try to adjust for such confounding factors through the design of the data collection or through the analysis of the observational data (or through a combination of both). Rosenbaum (2010) provides an overview of observational studies and Imbens and Rubin (2015) discuss approaches to causal inference with observational studies.

Examples of observational study designs that can help identify causal effects include cohort studies and case-control studies. In a cohort study, a set of individuals (perhaps drivers with sleep apnea) are identified and the causal factor of interest (e.g., frequency of use of sleep apnea treatment) is measured. The cohort is then followed prospectively (or records examined retrospectively) to estimate the effect of the factor of interest on outcomes (e.g., crashes). A case-control study identifies a set of cases (individuals) who experience an event of interest (e.g., a crash) for which data about a potential cause are available along with information on confounding factors. Then one attempts to identify controls (individuals) who did not experience the event of

interest (e.g., did not experience a crash) which match the cases on a set of possible confounding factors. The relative frequency of the potential cause is then compared across the two groups. Case-control studies have been used in studying crash risk, e.g., Dingus et al. (2016) applied the approach in a naturalistic driving study.

Analysis techniques for observational data use observed values of collected variables to achieve a fair and balanced comparison between the two groups of interest (treatment and control). The simplest approaches are regression models of various types that relate the outcome of interest to a factor of interest while controlling for potential confounders. This is relatively simple to apply and used often; however, it requires that the assumed regression model is a reasonable representation of the real situation. More modern methods, like propensity score methods and marginal structural models, weight or adjust observations taking into account the likelihood of an individual receiving the treatment of interest. With propensity score methods (Imbens and Rubin, 2015), the likelihood of receiving a particular treatment (in an observational data set) is modeled in terms of pre-treatment variables. Then the researcher chooses a subset of exposed and unexposed (or “treated” and “control”) individuals that have matching (or similar) propensities to compare, or individuals can be weighted by their propensity of receiving the treatment. Such methods create comparison groups (exposed and unexposed) that are balanced on the potential confounding factors. These methods only balance confounding factors that are measured; sensitivity analysis methods can be used to examine how sensitive results are to imbalance on unmeasured confounding factors (Rosenbaum, 2010). Other analysis techniques are possible depending on the specific circumstance: Regression discontinuity can be used when some treatment of interest is given only above (or below) a certain threshold (e.g., when sleep apnea symptoms hit a threshold); interrupted time series can be used when a change occurs at a given point in time; and instrumental variables can be used if there is an “instrument” that affects receipt of the exposure of interest but does not directly affect the outcome.

A recent congressionally-mandated, naturalistic study to evaluate the operational, safety, fatigue, and health impacts of CMV driver hours-of-service restart provisions (Dinges et al., 2015) illustrates how observational studies can be used to evaluate the effects of work-hour regulations and driver practices on fatigue and safety. The goal was to compare driver performance and fatigue between CMV drivers using a 1-night rest period before restarting the hours-of-service “clock” and those using a 2-night rest period. The study also compared those with fewer than 168 h (one week) between restart periods and those with more than 168 h. The study included 235 drivers, using electronic logging devices to gather data on driving and working hours, onboard monitoring systems to gather data on safety-critical events, wrist actigraphs to gather data on sleep-wake times, and smartphone apps for collecting self-reported driver behaviors and driver alertness measures (using the PVT-B mentioned in Section 5 below). A total of 3287 restart/duty cycle units were analyzed using a variety of regression models to control for potential confounders. The study did not find performance differences between drivers using 1-night restarts and 2-night restarts but drivers indicated greater fatigue and lower quality sleep during 1-night restarts. Driver response times were slower and attentional lapses more frequent when restarts occurred after more than 168 h versus prior to 168 h.

4. Long-term driver health

4.1. Data issues

FMCSA is also concerned about the impact of fatigue on the health of CMV drivers. There is a large literature relating insufficient sleep with health risk. For example *Sleep Disorders and Sleep Deprivation: An Unmet Public Health Problem* (Institute of Medicine, 2006) reports that long-term sleep loss and sleep deprivation is associated with increased risk of hypertension, diabetes, obesity, depression, cardiovascular

disease, and stroke. Importantly, the relationship can work in the opposite direction as well with certain diseases also increasing the risk of fatigue (Czeisler, 2015).

A framework similar to the one described by Table 1 in the context of driver safety is appropriate. The major differences are that we are focused on health outcomes rather than safety outcomes and that we would not expect environmental or vehicle characteristics to help predict or understand these outcomes.

There is limited data available about the health of the CMV driver population. Sieber et al. (2014) collected data on the behaviors, habits and health status of 1670 long-haul truck drivers. FMCSA's Commercial Driver Individual Risk Factors Study (CDIRFS) (Hickman et al., 2018) is a cohort study that collected demographic, medical, attitudinal, and behavioral data for more than 20,000 drivers who were then followed for up to three years. Though the ultimate aim of the CDIDS is to assess factors associated with crash risk (through a case-control design), the CDIDS cohort data collection provides a unique view of the driver population.

These studies can provide useful information, but to obtain a more complete understanding of driver health and the determinants of driver health it would be valuable to obtain longitudinal data on the population. The panel recommended that such data be gathered through a longitudinal study of a sample of drivers. Data should be collected concerning job characteristics (type of work, hours of work), lifestyle (sleep, diet and exercise habits), and medical conditions (weight, blood pressure, disease status, medications). Certain conditions and diseases like obesity, obstructive sleep apnea (OSA), and cardiovascular disease are common in the driver population. A longitudinal study would allow researchers to identify factors associated with CMV drivers developing these health issues. Though the longitudinal study is superior for addressing questions of this type, such studies can be costly and challenging to execute (especially given the turnover in the CMV driver population). Repeated cross-sectional studies may also be useful in providing regular information about the population and identifying trends in population behaviors and health.

Obstructive sleep apnea (OSA) is a health condition that requires special attention for CMV drivers due to the incidence of obesity in the population. In OSA, the airway becomes partially blocked during sleep, resulting in the subject waking frequently during the night. Thus, OSA is associated with insufficient sleep as well as with other medical conditions such as diabetes and cardiovascular diseases. OSA is a special concern for CMV drivers for several reasons. First, studies have estimated that 20% or more of CMV drivers have at least mild OSA (Pack et al., 2006; Berger et al., 2012). Second, there is a substantial literature that severe OSA is associated with increased crash risk for the non-professional driver (see Smolensky et al., 2011, for a summary). Though there is no corresponding literature on CMV drivers, the NASEM panel concluded that there is no reason to believe the increased crash risk would not apply to the CMV population as well (Chapter 8 in NASEM, 2016). This argues that there is a substantial need for data collection and research that can provide information regarding the prevalence of OSA, appropriate screening tools that might be used in the CMV medical examination, the relationship of OSA to driver safety (preferably as function of OSA severity), and the impacts of OSA treatment on driver health and safety.

4.2. Statistical methods

Longitudinal studies of the type recommended above would gather repeated observations of driver variables associated with health and fitness (e.g., frequency and duration of sleep, blood pressure, etc.). There is a rich literature of methods for longitudinal modeling (see, e.g., Diggle et al., 2002). Many of the topics discussed above in Section 3.2 regarding statistical methods for causal inference from observational data are relevant to longitudinal studies of driver health. The situation can be complex because of the possibility that exposure can vary over

time (e.g., severity of sleep apnea) as can the confounding factors. There can also be feedback between the exposure, outcome, and confounding factors over time (e.g., sleep can affect employment which can affect subsequent sleep). Robins and Hernán (2009) describe an approach to causal inference in longitudinal settings.

5. Evaluating technology and educational programs

A variety of technological developments including electronic on-board recorders, electronic logging devices, electronic data recorders, on-board safety systems, actigraphy and smart phones for real-time ambulatory monitoring of drivers, and telematics have the potential to radically transform the CMV industry and improve safety outcomes. Section 3.1 describes the potential benefit of data collected from such devices in understanding the link between fatigue and crash risk. In addition, there is the potential for technology to play a role in detecting driver fatigue (one example is real-time assessment of eyelid closure (Wierwille et al., 1994)), and assessing driver fitness for duty (e.g., the PVT-B psychomotor vigilance test (Basner and Dinges, 2011; Basner et al., 2011)).

The NASEM panel recommended that such technologies be carefully evaluated using a human-systems integration approach. The goal in such evaluations is to study the effect on drivers and crash risk while monitoring any unintended consequences of the technologies. One concern is whether the use of such technologies will modify driver behavior and decision-making (e.g., drivers may continue to drive despite being fatigued because of confidence in on-board safety systems). Thus, understanding driver decision-making should also be a priority.

Educational programs like NAFMP and incentive-based health programs may be useful in reducing CMV crashes by improving driver sleep behavior, health, and fitness. The latter use incentives or rewards for drivers who participate in health-promoting behaviors (e.g., joining a health club). As with a new technology, it is critical to carefully evaluate the effectiveness of such programs through rigorous studies. Surveys of NAFMP participants can be used to assess the knowledge obtained through the program and any (self-reported) resulting changes in behavior. For programs that are being developed, either randomized experimental studies or observational studies (designed and analyzed using the techniques described in Section 3.2) can determine effectiveness and identify potential improvements.

6. Discussion and conclusions

Understanding the relationship of CMV driver work schedules and fatigue, and their impact on highway safety and long-term driver health is a complex topic due to the presence of many confounding factors. Driver demographics and behavior, vehicle properties, carrier policies, and the environment can all contribute to crash risk. Thus it is imperative that studies attempt to gather relevant data and use appropriate methods to address these important questions. This article has, in summarizing the NASEM (2016) report, focused on a number of ways in which this might be done.

Section 2 outlines a comprehensive framework for assessing the factors that can produce fatigue and the factors that are related to crash risk and long-term driver health. Studies frequently rely on observed crash data to isolate factors associated with risk. Unfortunately existing crash data files are derived primarily from police accident reports which have only a limited number of variables recorded. It is important that as many relevant factors (driver, vehicle, carrier, environment) be obtained for such studies as possible, perhaps by combining data from multiple sources. Further, it is important to have data from non-crash drive-time in order to understand whether a factor is more prevalent in crash events than in non-crash events. As a result, improved data on exposure (i.e., the travel of CMVs and other vehicles) is critical for such analyses. To study long-term health, some kind of ongoing study of CMV drivers is critical. This will provide data on the incidence of

different health issues (e.g., OSA and cardiovascular disease) and their impact on long-term driver health.

Observational studies are the primary tool for assessing the determinants of fatigue and the relationship of fatigue to highway safety. As always, it is important with such data to ensure that comparisons adjust for potential confounding factors. Section 3.2 describes a number of statistical approaches that have proven useful in obtaining reliable inferences from observational data. New technologies and educational programs have the potential to provide novel data and to play a role in enhancing CMV driver health and safety. Careful evaluation of the effectiveness of educational programs or technological innovations is critical to make sure drivers find them helpful and that they do not have unintended consequences. Improving the available data and applying appropriate statistical methods have the potential to continue advancing knowledge about the factors associated with fatigue in CMV drivers, with the ultimate goal of reducing the impact of fatigue on highway safety and driver health.

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