EXPOSURE-RISK ANALYSIS OF LARGE TRUCK NATURALISTIC DRIVING DATA

Ronald R. Knipling
Virginia Tech Transportation Institute
7054 Haycock Road, #434
Falls Church, VA USA 22043
703-538-8439
rknipling@vtti.vt.edu

Richard J. Hanowski
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: 540-231-1513
hanowski@vtti.vt.edu

Jeffrey S. Hickman
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
(540) 231-1542
jhickman@vtti.vt.edu

Rebecca L. Olson
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
(540) 231-1584
rolson@vtti.vt.edu

Thomas A. Dingus
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
(540) 231-1500
tdingus@vtti.vt.edu

Robert J. Carroll
Federal Motor Carrier Safety Administration
400 Virginia Avenue, S.W. Suite 600
Washington, DC 20024
(202) 385-2388
robert.carroll@fmcsa.dot.gov

Naturalistic driving studies involving instrumented vehicles provide video and dynamic data on safety-relevant driving incidents, including crashes, near-crashes, and other crash-relevant conflicts. In addition to providing "instant replays" of these events, a major advantage of the naturalistic driving methodology is its potential to provide exposure and other data on normal, non-incident driving. "Baseline" data from naturalistic driving studies can document the parameters of driving conditions and the frequency of various driver behaviors and states. The comparison of baseline data with incident data permits a determination of the relative risk associated with various driving conditions and behaviors. Such comparisons and risk determinations are not normally possible for conventional crash data sets. Exposure-risk analysis employing odds ratios or other statistical comparisons may be the most scientifically rigorous approach to assessing the safety effects of various large truck driving conditions and driver behaviors. The FMCSA-sponsored Commercial Vehicle Data Collection and Countermeasure Assessment project has used naturalistic driving data from the NHTSA-sponsored Drowsy Driver Warning System Field Operational Test to explore the genesis and correlates of crashes, near-crashes, and crash-relevant conflicts, and differential driver risk. This paper reports highlights of the exposure-risk analysis, comparing the conditions of occurrence of these incidents to control data from analyst observations of randomly selected baseline driving epochs. Compared to baseline epochs (exposure), safety-critical events occurred much more frequently on non-divided highways, in construction zones, at or near intersections, on entrance/exit ramps, during daylight, and when traffic density was high. Extreme disproportionate risk was also observed among the 95 drivers in the study. This is the largest naturalistic driving study ever conducted on long-haul commercial driving, and is among the first to perform systematic exposure-risk analysis.

INTRODUCTION AND PROBLEM BACKGROUND

Under the sponsorship of the Federal Motor Carrier Safety Administration (FMCSA) and the National Highway Traffic Safety Administration (NHTSA), the Virginia Tech Transportation Institute (VTTI) has conducted several "naturalistic driving" instrumented vehicle studies involving commercial trucks. The FMCSA-sponsored Commercial Vehicle Data Collection and Countermeasure Assessment project (Hanowski et al., 2004; Hickman et al., 2005) is using data from the NHTSA-sponsored Drowsy Driver Warning System (DDWS) Field Operational Test (FOT) and planned additional data collection to gain new knowledge of the fundamental aspects of commercial vehicle safety, including heavy vehicle safety events, traffic conflict assessment, countermeasure identification, associations between driver alertness and safety performance, driving patterns and work/rest schedules, and correlates of driver risk. Phase I of the project has been completed, and includes data from 46 instrumented trucks and 95 volunteer commercial driver subjects encompassing almost 48,000 hours of driving data.

The analysis employed a database of classification variables used to compare the following basic types of driving events or incidents: crashes (14), tire strike "crashes" (14), near-crashes (98) crash-relevant conflicts (789), total safety-critical events (the sum of the previous, 915), and baseline (control) epochs (1,072). For simplicity, the current paper provides primarily aggregated event data for the 915 total safety-critical events, and compares these to baseline epochs. The full report (Hickman et al., 2005) provides data for all the above event categories.

Naturalistic driving studies provide important causation and risk data to compliment crash investigation studies such as the FMCSA/NHTSA Large Truck Crash Causation Study (LTCCS). Although most of the data obtained are for traffic incidents rather than actual crashes, these events can be reduced and analyzed "as if" they were crashes through the observation of recorded videos and associated dynamic data. The issue of validation of non-crash event data vis-à-vis crash data is beyond the scope of this paper, but there are undeniable similarities in conditions of occurrence, scenarios, and critical driver errors.

Another major advantage of naturalistic driving data is that control data can be readily obtained. Naturalistic driving studies like the current study are not experiments in the formal sense, since there is no manipulation of conditions. Nevertheless, comparing event data to control data (i.e., randomly selected time periods) provides a basis for assessing and quantifying the effects of various factors on the risk of event occurrence. Regardless of specific causal attributions, conditions differentially associated with event occurrence or non-occurrence reflect differential relative risk in those situations. Such event-baseline comparisons and risk quantifications are typically not performed for crash investigation data.

Another type of exposure-risk comparison is among different drivers – that is, high-risk drivers versus those with lower risk. A recent study (Knipling et al., 2004) reviewed the evidence for differential crash risk among commercial drivers and explored personal factors associated with differential driver risk. The current study provides additional strong evidence that risk is disproportionately distributed among drivers, with a relatively small percentage of drivers being associated with a major portion of aggregate risk.

METHODOLOGY

Instrumented vehicle data were collected from commercial trucks during the normal operations of three long-haul trucking companies. This included one truckload and two less-than-truckload operations. As indicated above, subjects were also participating in an experimental study of the DDWS and thus were assigned to either an experimental or control group. However, data for the two groups were similar and were generally aggregated for the incident causation analysis. All the data presented in the current paper are aggregated across all 95 participating Phase I drivers.

Forty-six (46) truck tractors were instrumented. A Data Acquisition System (DAS) was installed in tractors to collect data continuously whenever the trucks were on and in motion. Three types of data were collected continuously by the vehicle instrumentation: video, dynamic sensor, and audio. Four video cameras were oriented as follows: (i) forward road scene, (ii) backward from driver's face camera, (iii) rearward from the left side of the tractor, and (iv) rearward from the right side of the tractor (see Figure 1). Low-level infrared lighting (not visible to the driver) illuminated the vehicle cab so drivers' faces and hands could be viewed via the camera during nighttime driving. No cameras or other sensors were mounted on trailers; this limited the analysis to primarily those events occurring in front and at the sides of the instrumented vehicle. Recorded dynamic data included speed, longitudinal acceleration (e.g., indicative of braking levels), and lateral acceleration. Vehicles were also equipped with lane trackers, and forward-looking radar units. A pushbutton "incident box" microphone permitted drivers to make verbal comments about traffic incidents, but was rarely used by subjects.

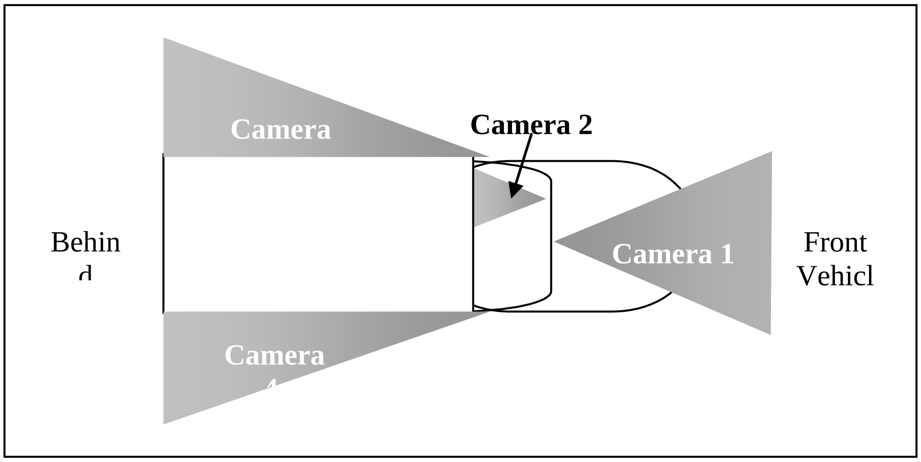

Figure 1. Camera directions and approximate fields-of-view.

There were three primary steps in detecting and classifying safety-critical events: (i) identifying potential events, mostly through the use of an event trigger program, (ii) checking the validity of these triggered events, and (iii) applying the data directory to verified conflict events. To identify events, a software program scanned the dynamic dataset to identify notable actions, including hard braking, quick steering maneuvers, and short times-to-collision. Threshold values of these parameters (or "triggers") were established to flag events for further review. In addition, a small number of events were flagged for review by the driver via the incident button and fortuitously by analysts reviewing non-flagged portions of the data. Because of the huge volume of data (~48,000 hours), there was no comprehensive review of all recorded driving data.

Events judged to be valid traffic conflicts were classified using a detailed data directory of 54 variables and associated data elements. This included classification variables relating to each overall event, to the subject vehicle or V1 (the truck) and driver, and (to a limited extent) the other involved vehicle/driver (V2) or non-motorist. Most of the variables were the same, or similar, to those used in major national crash databases such as the General Estimates System (GES) and the LTCCS.

For each driver subject during every week of driving, one 60-second baseline epoch was selected to create a control data set of normal driving. Traffic conflict-specific variables such as "critical event" and avoidance maneuver were not relevant to such baseline epochs, but events relating to the conditions of occurrence were relevant and were coded. This included variables such as time, day-of-week, weather, roadway type, and traffic conditions. Driver behaviors were also recorded, but this was limited to behaviors that might occur in normal driving (e.g., looking out the side window), as opposed to driving errors (e.g., failure to see a crash threat).

The comparison of safety-critical event and baseline statistics provided an assessment of the increased risk associated with the condition or behavior under examination. Odds ratios were used to compare the relative likelihood of a safety-critical event under particular circumstances (e.g., undivided highways) to the likelihood of the event under other circumstances (e.g., divided highways). These comparisons are the principal subject of this paper, although data are also presented comparing individual driver exposure to risk to document and quantify differential risk within driver subject pool. The full project report (Hickman et al., 2005) analyzes the various event types and aggregated events per all 54 variables, as well as comparisons to baseline epochs for all applicable variables.

RESULTS: SAFETY-CRITICAL EVENT ANALYSIS

Although event analysis *per se* is not the main topic of this paper, the study analyzed many variables relating to the characteristics and key dynamic events occurring within safety-critical incidents, such as pre-incident movements, critical events, critical reasons, avoidance maneuvers, and "accident" types (for non-crashes based on an extrapolation of the most likely crash type that could have occurred). Such variables are not applicable to normal, non-incident driving. But the 915 safety-critical events were analyzed in the same way that crashes would be analyzed per these variables. The most common "accident" types were those where V1 (the truck) was the potential striking vehicle in a rear-end crash. When the critical reason was assigned to V1, the most commonly cited reasons (in descending order) were inadequate evasive action, internal distraction, external distraction, misjudgment of gap or others speed, or too fast for conditions.

Review of video and other naturalistic driving data in this study and others has revealed a common sequence in many incidents: 1) unsafe pre-incident behavior or maneuver (e.g., speeding, tailgating, unsafe turn); 2) transient driver inattention (which may be related to driving, such as mirror use, or unrelated, such as reaching for an object); and 3) an unexpected traffic event, such as unexpected stopping by the vehicle ahead. Not all of these elements occur in every incident, but often two or all three are seen. As noted, the full report (Hickman et al., 2005) contains detailed data on multiple variables describing safety-critical events.

RESULTS: EVENT-BASELINE COMPARISONS ON SELECTED VARIABLES

A subset of study data for variables coded for both safety-critical events and baseline epochs is provided here. The percentages shown in the tables are column percentages for each category. As noted, only the aggregated data for the 915 total safety-critical events are shown in comparison to the control data (1,072 baseline epochs). The full study report contains data for all event categories and many more variables than are cited here.

Trafficway Flow (Divided vs. Undivided Roadway)

Table 1 displays the frequency and percentage of Trafficway Flow codes. Comparing baseline epochs to safety-critical events reveals a sharp difference in the distribution of locations; most notably, only 9.1% of baseline epochs occurred on the two categories of undivided roadway (i.e., 1.3% + 7.8%) versus 33.6% of safety-critical events. A Chi-Square statistical test was used to compare the two distributions. A 2 Event (Safety Critical Event, Baseline Epoch) X 5 Trafficway Flow [Not physically divided (center 2-way turn lane, Not physically divided (2-way trafficway), Divided, One-Way Trafficway, Unknown] Chi-Square showed a highly significant difference ($X^2_{(4)} = 222.441$, $p < .001$). The proportions of all trafficway flow conditions other than "divided" were higher for safety-critical events than for baseline epochs.

An odds ratio was calculated to compare the relative risk associated with "other" versus divided. The odds ratio is a way of comparing whether the probability of a certain outcome is the same for two conditions. In this analysis, the two outcomes are safety-critical events ("incidents") and baseline epochs ("non-incidents"). An odds ratio of 1 would imply that the outcome was equally likely under both conditions. An odds ratio greater than one would imply that the outcome was more likely in the first condition while an odds ratio of less than one would imply that the outcome was less likely. The odds ratio for "other" versus divided highways for incidents versus baseline epochs is provided by reduction of the following expression: ([48+260+40+8]/[14+84+15+0])/(559/959) = (356/113)/(559/959) = 5.4. This indicates that drivers were 5.4 times more likely to be involved in an incident if they were *not* on a divided highway. Like most statistics, this odds ratio is a best estimate with a surrounding margin of error or confidence interval. For brevity, these are not provided in the current analysis.

Table 1. Frequency and percentage of Trafficway Flow conditions.

Trafficway Flow:	Total Safety Critical Events		Baseline Epochs	
Divided	559	61.1%	959	89.5%
Not physically divided (center 2-way turn lane)	48	5.2%	14	1.3%
Not physically divided (2-way trafficway)	260	28.4%	84	7.8%
One-way trafficway	40	4.4%	15	1.4%
Unknown	8	0.9%	0	0.0%
Total	**915**	**100.0%**	**1072**	**100.0%**

Construction Zones

Observation of baseline epochs indicated that trucks were in construction zones or in "related" areas less than 1% of the time, but a total of 6.0% of detected safety-critical events occurred in these areas. While 6.0% is not a large percentage, the relative difference between the two percentages (event and baseline) indicated that this was a significant factor increasing *relative* risk. A Chi-Square comparison indicates that these two distributions were significantly different at $p < .001$. The odds ratio of safety-critical events versus baseline epochs in construction zone or related locations compared to non-construction or unknown locations was 8.5.

Table 2. Frequency and percentage of Construction Zone conditions.

Construction Zone Related:	Total Safety Critical Events		Baseline Epochs	
Not construction zone related	859	93.9%	1 064	99.3%
Construction zone	43	4.7%	7	0.7%
Construction zone related	12	1.3	1	0.1

		%		%
Unknown	1	0.1%	0	0.0%
Total	**915**	**100.0%**	**1072**	**100.0%**

Similar large differences between event and baseline incidence were observed for other types of "non-normal" highway locations. For example, the percentages of safety-critical events occurring at intersections and on entrance-exit ramps were many times the corresponding baseline epoch percentages for these locations. It is clear that normal, non-junction sections of roadway were associated with low risk, while areas with restricted geometry and/or likely interaction with other vehicles had greatly increased relative risk.

Traffic Density

"Level of Service" (LOS) is a subjective variable that characterizes traffic density, or, more specifically, the degree of restriction of vehicle movement due to the presence of other vehicles on the roadway. LOS A indicates that a vehicle's travel is unaffected by other vehicles; higher levels indicate higher degrees of restriction. The majority of both safety-critical events and baseline epochs occurred under unrestricted "A" conditions, but one can see in Table 3 that higher traffic densities were associated with greater probabilities of event involvement. The distribution differences were statistically significant at $p < .001$, and the odds ratio for event involvement for high traffic density (LOS C-F) versus low density (LOS A-B) was 5.9.

Table 3. Frequency and percentage of Traffic Density (Level of Service) conditions.

Traffic Density:	Total Safety Critical Events		Baseline Epochs	
Level of Service A	543	59.3%	778	72.6%
Level of Service B	216	23.6%	258	24.1%
Level of Service C	99	10.8%	33	3.1%
Level of Service D	37	4.0%	3	0.3%
Level of Service E	16	1.7%	0	0.0%
Level of Service F	3	0.3%	0	0.0%
Unknown	1	0.1%	0	0.0%
Total	**915**	**100.0%**	**1072**	**100.0%**

Light Condition

Event occurrence was also found to be related to light condition, but perhaps not in the direction that most would expect. The majority of both safety-critical events and baseline epochs occurred during daylight, but the event daylight percentage (73.4%) was *higher* than the baseline daylight percentage (56.4%). Conversely, the percentages for dark and various other light conditions tended to be lower for events than baseline epochs. The distributions were significantly different at $p < .001$, and the event involvement odds ratio of daylight to all other conditions was 2.1. That is, risk was *greater* during daylight. This finding probably reflects the increased traffic density generally found during daylight hours, although the data have not yet been analyzed in-depth to verify this interpretation. If this interpretation is confirmed, it would mean that, for the types of events captured, daytime traffic density generates more risk for trucks than do nighttime factors like driver fatigue and reduced visibility.

Table 4. Frequency and percentage of Light Conditions.

Light Condition:	Total Safety Critical Events		Baseline Epochs	
Daylight	672	73.4%	605	56.4%
Dark	164	17.9%	402	37.5%
Dark but lighted	61	6.7%	38	3.5%
Dawn	7	0.8%	15	1.4%
Dusk	11	1.2%	12	1.1%
Total	**915**	**100.0%**	**1072**	**100.0%**

Time-of-Day

Time-of-day relates to various other factors, including light condition, traffic, operational schedules, and fatigue. For time-of-day analysis, the 915 safety-critical events were disaggregated into 625 multi-vehicle and 290 single-vehicle events. The occurrence of multi-vehicle events compared to baseline exposure was strongly related to time-of-day ($p < .001$), with hours from 23:00 to 6:00 (11pm to 6am) significantly underrepresented and other times generally overrepresented. This overrepresentation begins in the mid-morning, peaks during the evening rush hours, and subsides during the evening. In contrast, the distribution of single vehicle events was not significantly different from the baseline distribution. Figure 2 shows three-hour rolling averages of the percent distributions of baseline epochs, multiple vehicle events, and single vehicle events.

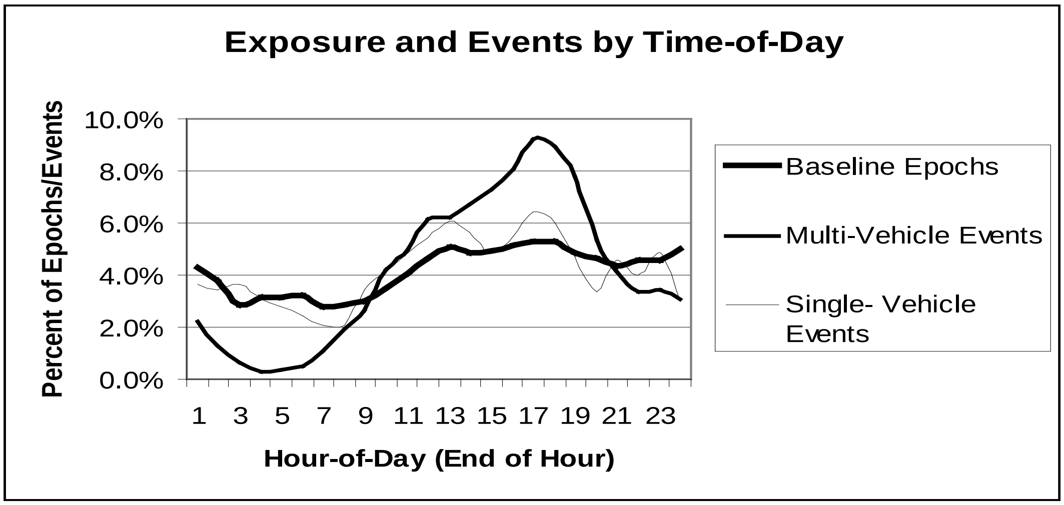

Figure 2. Percent distribution of baseline epochs, multi-vehicle events, and single-vehicle events by time-of-day (3-hour rolling averages)

Weather

One might expect adverse weather conditions to be associated with increased probabilities of safety-critical events, but this was not the case in the current data set. Table 5 shows that the vast majority of both safety-critical events and baseline epochs occurred during clear conditions. What is surprising, perhaps, is that the two distributions were almost identical and were not significantly different statistically. A larger data set might well show increased risk associated with extreme conditions like snow and sleet, but there were not sufficient events or baseline epochs in the current data set to demonstrate this.

Safety Belt Use

Driver safety belt use was recorded based on observation of each event and baseline epoch, and was less than 60% for each category. The question of primary interest, though, was whether safety belt use would be associated with greater risk of event involvement. This might reflect driver personality tendencies; i.e., belt use associated with conscientiousness and caution and non-use associated with risk-taking. Other studies have indeed cited such behavioral tendencies associated with belt use or non-use (Lancaster and Ward, 2002). However, in the current study

Table 5. Frequency and percentage of Weather conditions.

Weather:	Total Safety Critical Events		Baseline Epochs	
No adverse conditions	859	93.9 %	99 5	92.8 %
Rain	47	5.1 %	69	6.4 %
Sleet	1	0.1 %	1	0.1 %
Snow	3	0.3 %	3	0.3 %
Fog	3	0.3 %	2	0.2 %
Rain and fog	2	0.2 %	1	0.1 %
Sleet and fog	0	0.0 %	0	0.0 %
Other	0	0.0 %	1	0.1 %
Total	**915**	**100. 0%**	**10 72**	**100. 0%**

the distribution of belt use for total safety-critical events was not significantly different than the baseline distribution ($p > .05$). In Table 6 the two distributions are very similar. However, recall that the 915 safety-critical events included 789 less severe "crash-relevant conflicts" and a total of 126 more severe events including crash, tire strikes, and near-crashes. In these 126 more severe events (not shown separately in Table 6), only 59 drivers (46.8%) were belted versus 67 (53.2%) who were not. When the baseline distribution was compared to this distribution for more severe events, a significant difference was observed at the $p < .02$ level of significance. This lends some credence to the idea that driver non-use of safety belts is associated with other risky driving behaviors. Further, when the combined crashes, tire strikes, and near-crashes were disaggregated by at-fault versus not-at-fault, approximately 45% of the at-fault truck drivers were observed to be wearing belts, versus 58% of the not-at-fault truck drivers. However, this difference was not statistically significant at $p < .05$.

Table 6. Frequency and percentage of Safety Belt use.

V1 Driver Wearing Safety Belt:	Total Safety Critical Events		Baseline Epochs	
Yes	504	55.1 %	62 5	58.3 %
No	409	44.7 %	44 4	41.4 %
Unknown	2	0.2	3	0.3

		%		%
Total	915	100.0%	1072	100.0%

RESULTS: DIFFERENTIAL DRIVER RISK

Another exposure-risk question relates to differences among drivers. That is, is crash risk significantly greater for some driver than for others? Based on other recent analyses (e.g., Knipling et al., 2004, Knipling, 2005), the answer to this question appears to be a resounding "yes." There appears to be sharp differential crash risk among commercial drivers and also sharp differences in fatigue susceptibility while driving.

In the current study, three principal metrics of driver risk were employed to assess individual driver risk and then to compare drivers:

- Rate of involvement (per hour of driving) in "at-fault" events (i.e., crashes + near-crashes + crash-relevant conflicts, 680 total)
- Rate of involvement in *not*-at-fault events (235 total)
- Rate of involvement in high driver drowsiness events regardless of fault. "High-drowsiness" was defined as an Observer Rating of Drowsiness (ORD) of 40+ on a 100-point scale. There were 127 such high-drowsiness incidents.

To document and quantify differential driver risk, individual driver risk rates for each of these three metrics were calculated and then arranged in descending order. Within each metric, the worst 15 (15.8% of the 95 subjects) drivers were compared to the middle 40 (42.1%) and the best 40 (42.1%). A summary of the differential risk rates for these three metrics follows:

- At-fault events (i.e., truck driver assigned "critical reason"; 680 total):
  - Worst 15 drivers: 11.0% of driving hours → 38.2% of at-fault events
  - Middle 40 drivers: 46.7% of driving hours → 54.1% of at-fault events
  - Best 40 drivers: 42.3% of driving hours → 7.6% of at-fault events
- Not-at-fault events (i.e., other driver assigned critical reason; 235 total):
  - Worst 15 drivers: 14.6% of driving hours → 43.0% of not-at-fault events
  - Middle 40 drivers: 50.4% of driving hours → 51.9% of non-at-fault events
  - Best 40 drivers: 34.9% of driving hours → 5.1% of not-at-fault events
- High-drowsiness events (includes both at-fault and not-at-fault incidents; 127 total):
  - Worst 15 drivers: 14.6% of driving hours → 69.3% of drowsy events
  - Middle 40 drivers: 49.5% of driving hours → 30.7% of drowsy events
  - Best 40 drivers: 35.9% of driving hours → zero drowsy events.

Another way of illustrating the safety significance of high-risk drivers is to calculate the relative exposure-risk ratios for the worst 15 drivers on each parameter compared to the other 80 drivers on that parameter. These ratios were as follows:

- Ratio of at-fault involvement rates: 5.0
- Ratio of not-at-fault involvement rates: 4.4
- Ratio of drowsy event involvement rates: 13.2.

These distributions strongly demonstrate differential driver risk, and support the notion that a small percent of drivers in almost any group of drivers are associated with a grossly disproportionate amount of aggregate risk. As found in previous studies, this was true for at-fault events and for high-drowsiness events. Surprisingly, perhaps, it was also true of not-at-fault events, perhaps indicating that defensive driving skills also vary greatly among drivers. Moreover, there were moderately high intercorrelations (+0.55 to +0.67) among these three metrics, indicating that drivers who were high-risk per one metric tended to be high-risk on other metrics as well.

In fairness to those drivers classified as “worst” per the above metrics, it may be noted that these data were collected in actual trucking operations that were not tightly controlled experimentally. Uncontrolled factors potentially contributing to the observed effects could include route differences (e.g., road design, traffic density) and/or other confounding factors influencing the safety performance of different drivers in the study.

DISCUSSION

Two major advantages of the naturalistic driving methodology are the large amount of safety-related data that can be obtained (because incidents are far more numerous than crashes) and the fact that events can be directly observed like a sports "instant replay" rather than reconstructed *post hoc*. A third advantage is that baseline exposure or "denominator" data can be obtained readily along with event or "numerator" data. In formal experimentation, the comparison of experimental groups to control groups permits causal inference about the effects of manipulated independent variables on measured dependent variables. Although the current data were collected in the context of an experimental test of a safety technology (the DDWS), the data presented in this paper and in the Phase I report do not relate to this technology experiment but rather to the driving that took place as the backdrop to the experiment. None of the factors cited here (i.e., trafficway flow, construction zones, traffic density, light condition, time-of-day, weather, safety belt use) were controlled or manipulated – rather these conditions occurred naturally. In this design, causal inference is possible from the comparison of the prevalence of conditions under which unfavorable outcomes occurred (i.e., crashes, near-crashes, and other safety-critical events) to the baseline prevalence of such conditions. When the event and baseline distributions were significantly different, it was inferred that the condition or other factor under consideration was associated with increased or decreased safety risk. Odds ratios were used to quantify the change in risk associated with that condition or factor. The delineation and quantification of crash risk factors may be considered conceptually in multi-factorial models of crash causation, but more cogently the data have direct implications for transport operations. The findings of this paper imply that motor carrier fleets and drivers should, to the greatest extent possible, seek to avoid undivided highways, construction zones, dense traffic, and evening rush hours. While all of these factors were likely already known as risk-elevating conditions, the extent of the risk elevation is not easily known based on crash or incident data alone. Comparisons of event data to exposure data is needed to verify these conditions as risky and to quantify the risk. Also, in at least two cases (rain and overnight driving), the data showed that conditions commonly regarded as risky were not actually associated with increased risk, at least for the types of incidents detectible through the vehicle instrumentation and analysis of dynamic triggered events.

Some of the results of this exposure-risk analysis must be interpreted with caution. For example, the finding that risk is greater under daylight than dark conditions does not necessarily imply that higher visibility reduces safety. Top-level data on this variable incorporate all of the factors that co-vary with daylight (most notably, traffic density) as well as light level itself. Various associated factors can be isolated through disaggregation of the data by co-varying factors such as traffic density, although the current data set is not sufficiently large for granular disaggregations. Even at macro levels, however, these kinds of findings still have safety significance because they have practical implications. In this case, the "bottom line" implication is that daytime driving may actually be riskier for large trucks than nighttime driving.

Most of the exposure data presented in this paper could not feasibly be gathered through traditional exposure data systems such as traffic counts, logs, or surveys. Classifying crashes by such factors as trafficway flow, occurrence in a construction zone, and weather conditions is easy, but obtaining accurate and representative exposure data relating to such factors through conventional means would be very difficult and/or prohibitively expensive. Thus, fundamental safety questions such as whether driving in the rain is more dangerous than driving in sunshine have never been answered definitively.

Just as certain driving conditions are associated with elevated risk, certain drivers appear to have greatly elevated risk. In the case of high-drowsiness events, the worst 15 drivers had an average rate of involvement that was 13 times the average of the other 80 drivers. National and state crash and violation data for drivers contain no mileage or other exposure data; thus driver data cannot normally be analyzed as rates but rather as raw numbers or probabilities. Differential exposure is a major confound in commercial driver safety data, since long-haul drivers may drive ten times as far per year as short-haul or utility drivers. On the three driver risk metrics cited, 15 of the 90 drivers (17%) accounted for 38-69% of aggregated group risk. Hours of driving was collected as an exposure measure, and so these drivers could be identified as having the highest rates of involvement in the various types of incidents. Other data collected in the study, and to be collected in future studies, are relating the observed differential risk among drivers to their personal traits and driving behaviors in order to seek means for predicting individual driver risk and interventions to reduce it.

REFERENCES

Hanowski, R.J., Knipling, R.R., Hickman, J.S., Schaudt, A.W., Olson, R.L, & Dingus, T.A. (2004) *Phase 1 - Preliminary Analysis of Data Collected In The Drowsy Driver Warning System Field Operational Test: Task 1, Preliminary Analysis Plan*, for the FMCSA under NHTSA Contract DTNH22-00-C-07007, TO #21.

Hickman, J.S., Knipling, R.R., Olson, R.L., Fumero, M., Hanowski, R.J., & Blanco, M. (2005) *Phase 1 - Preliminary Analysis of Data Collected In The Drowsy Driver Warning System Field Operational Test: Task 5, Phase I Data Analysis*, for the FMCSA under NHTSA Contract DTNH22-00-C-07007, TO #21.

Knipling, R.R. Evidence and dimensions of commercial driver differential crash risk. *Proceedings of the Driving Assessment 2005 Conference*. Rockport, ME, June 27-30, 2005.

Knipling, R.R., Boyle, L.N., Hickman, J.S., York, J.S., Daecher, C., Olsen, E. C. B., and Prailey, T.D. (2004) *Synthesis Report #4:   Individual Differences and the High- Risk Commercial Driver*. Project Final Report, Transportation Research Board Commercial Truck & Bus Synthesis Program. ISSN 1544-6808, ISSN 0-309-08810-0.

Knipling, R.R. and Hickman, J.S. (2005) Surveys on carrier safety management problems, high-risk drivers, & management solutions. Paper and presentation for the *2005 Truck & Bus Safety & Security Symposium*, Alexandria, VA, November 14-16, 2005.

Lancaster, R. and Ward, R. (2002) *The contribution of individual factors to driving behaviour: Implications for managing work-related road safety.* Entec UK Limited, Health and Safety Executive, Research Report 020, United Kingdom.

Citation: Knipling, R.R. Hanowski, R.J.; Hickman, J.S., Olson, R.L., Dingus, T.A. and Carroll, R.J. Exposure-risk analysis of large truck naturalistic driving data. *Proceedings of the 2005 Truck & Bus Safety & Security Symposium*, Alexandria, VA, November 14-16, 2005.