Effects of Hours of Service and Driving Patterns on Motor Carrier Crashes

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There is a need to explore the relationship, if any, between the probability of a crash and the hours worked by truck drivers. The need arises from the continued adjustment of federal hours of service regulations for truck drivers. This research used data logs from less-than-truckload carrier operations in 2004 to 2005 and in 2010 to estimate the probability of a crash after a certain amount of time spent driving, given no crashes until that time. Driver logs for 7 days before each crash were used and compared with a random sample (two drivers) of drivers who did not crash and were selected from the same company, terminal, and month. This study involved 686 subjects, including 224 crash-involved drivers. Discrete-time survival analysis models indicated a consistent increase in crash odds as driving time increased beyond the fourth hour. Breaks from driving reduced crash odds by as much as 50% compared with situations of drivers with no breaks. Crash odds were lowest when drivers returned to work during the day without an immediately preceding extended recovery period (but with at least minimum required off-duty time). Drivers returning to work immediately after a 34-h recovery period had crash odds 50% to 150% higher than those for drivers without the recovery immediately before a trip. Drivers had the highest crash odds immediately after returning from the extended time off; the effect then diminished with time.

Research on the safety implications of truck driver work hours was investigated in pioneering research during the 1970s (e.g., *1, 2*). A major field study was concluded in 1996 involving drivers who drove regular routes for their firms while also taking a variety of alertness tests and being subjected to other driving measurements (*3*). While the studies in the 1970s used crash and other operations data as the dependent measure, the 1996 report used alertness tests and measures of driving performance other than crashes. Throughout the 1990s, a series of studies were conducted comparing crash and noncrash drivers using data from a national less-than-truckload carrier (*4–9*). A subsequent paper (*10*) compared findings from an analysis of the crash data set from the 1980s and the experimental data collected by Wylie et al. (*3*). Campbell and Hwang also conducted a study of fatigue and crash odds using fatal crash data from 1991 to 2002 (*11*).

The aforementioned studies reveal one of the challenges in conducting research in truck safety and hours of service: Studies have found differing effects of driving hours. Several studies using crash data have found increased crash odds (or relative risk) with hours driving, particularly after about 5 to 6 h; increased crash odds were found in studies by Harris and Mackie (*1*) and Mackie and Miller (*2*); by Jovanis and Chang (*4*) and Chang and Jovanis (*5*); by Jovanis et al. (*6*); by Kaneko and Jovanis (*7*); by Lin et al. (*8*, *9*); by Park et al. (*10*); and by Campbell and Hwang (*11*). Studies by Frith (*12*) and Saccomanno et al. (*13*) also found association between driving hours and increased crash odds. By contrast, the 1996 study (*3*), using alertness tests and instrumented truck measures rather than crashes, found stronger correlation between fatigue and time of day, and little correlation between fatigue and driving hours. Many other researchers have also found elevated crash odds with night and early morning driving (*2, 7, 14,* and *15*). Klauer et al. conducted an experiment with 30 solo drivers and 13 team drivers with data measured both objectively and subjectively, finding evidence of fatigue for team drivers only in the morning and night hours, while solo drivers indicated fatigue throughout the day and night (*16*). This study used critical incidents rather than crashes as the indicators of crash risk.

FMCSA changed truck driver hours of service in 2003, extending driving time from 10 to 11 h, reducing maximum consecutive on-duty time to 14 h, and mandating that the time run continuously from the start of on duty time (i.e., off-duty time cannot extend the 14-h period). The minimum time off duty between driving periods was also increased from 8 to 10 h. For carriers in the data set, the maximum on-duty time is 70 h over 8 days, with a new 70-h period starting if the driver had 34 h or more consecutively off duty.

The objective of this research is to study the effect of hours of service rules on road safety, particularly aspects of the hours of service rule that changed in 2003, such as the maximum driving time and the treatment of on-duty not driving as continuous. Other areas of investigation include the effects of driving breaks, length and timing of the recovery period, and any interactions between driving time and time of day.

The analysis framework for the study is described in the next section, including a description of the statistical models and application of cluster analysis to the development of multiday driving patterns. The data section describes the data used in the study including the derivation of the predictor variables. The last two sections describe the results, followed by conclusions and implications for future research.

METHODOLOGY

This section contains a description of the application of cluster analysis in development of multiday driving patterns for each driver and a summary of the survival formulation basic to estimation of crash odds ratios.

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Driver logs are obtained for 7 days before the crash day, and a random sample of two noncrash drivers is selected from the same terminal in the same month for each crash-involved driver (*6–10, 17, 18*). Cluster analysis is applied to all the drivers (both crash-involved and controls) for the 7 days, to characterize their driving pattern over multiple days. The dependent variable for survival analysis is a crash or noncrash after driving a certain number of hours on the eighth day (referred to as day of interest).

Developing Multiday Driving Patterns with Cluster Analysis

Each truck driver on the road experiences a particular driving pattern over the 8-day period (or more) of measurement. At the level of the 15 min typically reported for each hour of each day, there are many possible driving patterns over multiple days; one then has the challenge of identifying drivers with similar multiday patterns so that they may be combined for manageable statistical analysis. Cluster analysis has been successfully used to group drivers into relatively consistent multiday driving patterns in previous studies (*6–10, 17*) and is employed in this study as well.

The input to the method is the duty status of every driver for every 15 min of every day during the 7-day duration before the day of interest. These data are input to the *k*-means clustering algorithm of Statistical Package for the Social Sciences, by using a prespecified range of cluster outputs (ranging from 6 to 11). Ten clusters were selected by the study team to represent multiday driving on the basis of minimum of 30 observations in each cluster and having the clusters indicate clear patterns of driving (where clarity is judged by having more than 50% of the drivers on duty over multiple days). These sample size limits are based on experience in previous studies applying the cluster analysis method to similar crash data on truck drivers. The outcome of the trip of interest (i.e., a crash or noncrash) does not affect the allocation of drivers to clusters. The only variables that influence the allocation of drivers to clusters are individual patterns of driving for each driver over the 7 days before the day of interest.

Discrete-Time Survival Analysis: Modeling Crash Odds

Discrete-time hazard, h_{ij}, is defined as the conditional probability that driver i will experience a crash in hours of driving j, $j = 1, 2, \ldots, 11$, given that the driver did not experience a crash before j (*7–9, 19*). Driver i's value for each of the P-predictors in time period j is denoted as the vector $z_{ij} = [z_{1ij}, z_{2ij}, \ldots, z_{pij}]$, and thus

$$h_j = \Pr\left(T = j \,|\, T \geq j, Z_{1ij} = z_{1ij},\ Z_{2ij} = z_{2ij}, \ldots, Z_{Pij} = z_{Pij}\right) \tag{1}$$

T is the hours driving at the time of the crash.

Since h_{ij} are probabilities, they can be expressed with a logistic formula:

$$h_{ij} = \frac{1}{1 + e^{-\left[\left(\alpha_1 D_{1ij} + \alpha_2 D_{2ij} + \cdots + \alpha_J D_{Jij}\right) + \left(\beta_1 Z_{1ij} + \beta_2 Z_{2ij} + \cdots + \beta_P Z_{Pij}\right)\right]}} \tag{2}$$

where

$D_{1ij}, D_{2ij}, \ldots, D_{Jij}$ = sequence of indicator variables, with values $d_{1ij}, d_{2ij}, \ldots, d_{Jij}$] indexing hours of driving;

J = last hours of driving observed for anyone in sample;

$\alpha_1, \alpha_2, \ldots, \alpha_J$ = intercept parameters that capture baseline level of hazard in each hour of driving; and

$\beta_1, \beta_2, \ldots, \beta_P$ = slope parameters that describe effects of predictors, either time-varying or time-independent, on the baseline hazard function.

For driver i who encountered a crash in hours of driving j_i but the crash did not occur in the first hour of driving through $j_i - 1$, Equation 1 can be written as follows:

$$\begin{aligned} Pr\left(T_i = j_i\right) &= Pr\left(T_i = j_i \,\middle|\, T_i \geq j_i\right) \times Pr\left(T_i \neq j_{i-1} \,\middle|\, T_i \geq j_i - 1\right) \\ &\quad \times \cdots \times Pr\left(T_i \neq 2 \,\middle|\, T_i \geq 2\right) \times Pr\left(T_i \neq 1 \,\middle|\, T_i \geq 1\right) \\ &= h_{ij_i} \times \left(1 - h_{i(j_i-1)}\right) \times \left(1 - h_{i(j_i-2)}\right) \times \cdots \times \left(1 - h_{i2}\right) \\ &\quad \times \left(1 - h_{i1}\right) = h_{ij_i} \prod_{j=1}^{j_i-1} \left(1 - h_{ij}\right) \end{aligned} \tag{3}$$

The $(1 - h_{ij})$ term in Equation 3 shows the need of data replications for periods without a crash occurrence for each individual driver i. Similarly, for noncrash drivers, referred to as censored in survival analysis, the probability of no crash occurrence given j hours of driving is as follows:

$$Pr\left(T_i = j_i\right) = \prod_{j=1}^{j_i} \left(1 - h_{ij}\right) \tag{4}$$

Therefore, by using Equations 3 and 4, the likelihood function can be described as follows:

$$L = \prod_{i=1}^{n} \left\{ \left[h_{ij_i} \prod_{j=1}^{j_i-1} \left(1 - h_{ij}\right) \right]^{1-c_i} \left[\prod_{j=1}^{j_i} \left(1 - h_{ij}\right) \right]^{c_i} \right\} \tag{5}$$

where

n = total drivers included in study,

$1 - c_i$ = crash-involved driver, and

c_i = a noncrash driver.

DATA

Data from less-than-truckload (LTL) carriers collected in 2004 and 2005 (*18*) were combined with additional data from carriers in 2010 to enhance efficiency of estimation. Statistical tests were performed to determine whether it is appropriate to combine the data from 2004 to 2005 and 2010. The study team was concerned that there might be differences in the factors contributing to crashes, since 5 to 6 years elapsed between the data collection periods. A series of Chow tests were performed to compare the two data sets (i.e., tests comparing models similar to those shown in Table 4, to be discussed later). The tests indicate limited evidence to support the position that the two sets of data are drawn from data with different underlying crash associations: The first Chow test (with driving time only as a predictor) rejects the null hypothesis, but addition of additional predictors leads to an inability to reject the null. The study team concluded that crash models of the type developed in this study could be developed with consolidated data sets across 2004 to 2005 and 2010.

TABLE 1 Data Analyses of Sample Size

Source of Data	Crash	Noncrash	Total
Firm 1 (2004–2005)	45	90	135
Firm 2 (2004–2005)	79	188	267
Firm 3 (2010)	100	184	284
Total	224	462	686

Sources of the driver data are carrier electronic or paper files retained either by the carrier or a third party. As in previous studies (*6–10, 17*), this is a case-control formulation, as shown in Table 1. All of the carriers involved in the study were large national-scale carriers; they might be characterized as being representatives of the trucking industry that are organized to generally adhere to the existing hours-of-service policies in effect at the time. While it is possible that manipulation of the data has occurred, the authors believe it is unlikely.

Table 1 summarizes the sample sizes obtained from each of the three carriers participating in the 2004 to 2005 and 2010 time periods (one carrier provided data for both time periods). While data were collected for two noncrash drivers for each crash-involved driver, missing data led to a final data set with less than the targeted 2:1 ratio. Attempts were made to obtain missing data from the carriers, but generally the data initially received were what were available.

DATA ANALYSIS

Data analysis begins with a description of the multiday driving patterns that evolved from application of the cluster analysis. A summary of the modeling results from the research follows discussion on the driving pattern.

Multiday Driving Patterns

Table 2 shows the number of crash and noncrash observations and the relative risk for each driving pattern. Pattern 4 is chosen as the baseline because it has the highest proportion of crashes in the data set. Pattern 4 and 5 drivers have relative crash risk above 0.9. Patterns 3, 8, and 9 have relative crash risks above 0.7, while Patterns 1, 6, and 10 have relative crash risks below 0.6.

TABLE 2 Relative Risk of Crash for Clusters

Driving Pattern	Crash	Noncrash	Total	Relative Crash Risk
1	19	58	77	0.555
2	22	58	80	0.619
3	41	74	115	0.802
4	36	45	81	1.000
5	27	38	65	0.935
6	19	63	82	0.521
7	15	34	49	0.689
8	21	35	56	0.844
9	13	24	37	0.791
10	11	33	44	0.563
Total	224	462	686	na

NOTE: na = not applicable.

Figure 1 graphically depicts each driving pattern. The horizontal scale depicts the 7 days before the day of interest, with the day immediately before that day of interest occurring at hours 168 of the graph. Time moves back from that point, so that the 7th day of driving is between hours 144 and 168, the 6th day of driving is between hours 120 and 144, and so forth, until the first day of driving for the 8-day period is shown as hours 0 to 24. The vertical scale is the percentage of drivers within the pattern who were driving or on-duty not driving during that particular day and time. The graph thus concisely summarizes the duty status of the drivers within that pattern. While the patterns were determined by using on-duty time as one category and all other time as the other (i.e., a dichotomous variable), the graphics include separate depictions of off-duty and sleeper berth times, to aid in interpretation.

The following observations summarize the key attributes of each pattern. On-duty time is referred to for ease of exposition, but the time includes driving time and on-duty and not-driving time, and the time is intended to be compared with the maximum cumulative hours of service of 70 h in 8 days.

- Pattern 1 has little on-duty or driving time in the first 3 days, but then regular driving is from around midnight at the end of day 3 until the end of day 7. While the proportion of drivers decreases somewhat from days 3 to 7, it is still 70% at midnight at the end of day 7. Off-duty time mirrors on-duty time, for there is minimal use of sleeper berth by drivers in this pattern. This driving pattern has the second lowest relative risk, at 0.56.
- Pattern 2 is a regular pattern with on-duty time centered on midnight, particularly at the beginning of day 1 and the end of days 4 to 7. The pattern is regular; almost 100% of drivers are on duty around midnight and off duty around noon on the days when scheduled to work. There is little use of sleeper berth by drivers; virtually all drivers are off duty from the end of day 2 to the end of day 4. This pattern has a relative risk of 0.62.
- Pattern 3 has work centered at midnight, in this case, at the beginning of day 1 and then again at the end of days 1, 2, 6, and 7. There is substantial (100%) off-duty time in midday on day 3, then again from midday on day 4 through the end of day 5. There is little use of sleeper berth by any driver in this pattern. Some drivers are working at the end of days 3 and 5, but only about 50% of those in the pattern. Pattern 3 has a crash relative risk of 0.80.
- Pattern 4 has the highest relative risk (1.00) and has regular work time (particularly days 1 to 4) centered on midnight and ending near noon. There is little working time on day 5 and even less on day 6. Drivers return to work at the end of day 7. Patterns 1 and 2 involve night driving, but those patterns have a low relative risk, while Pattern 4 has a similar pattern with respect to time of day, but a high relative risk. The difference is when the recovery period occurs before the trip.

An insight concerning crash odds can be gleaned by examining the trend in on-duty time across Patterns 1 to 4 (see Figure 1). One can see the progression of the recovery period moving from earlier in the multiday driving period in Pattern 1 to just before the day of interest in Pattern 4.

The relative crash risk increases as the recovery period comes closer to the day of interest (hour 168), starting at 0.56 and increasing to 1.0 when the recovery occurs on day 7. Drivers seem to have increased odds of a crash when immediately returning from a recovery period.

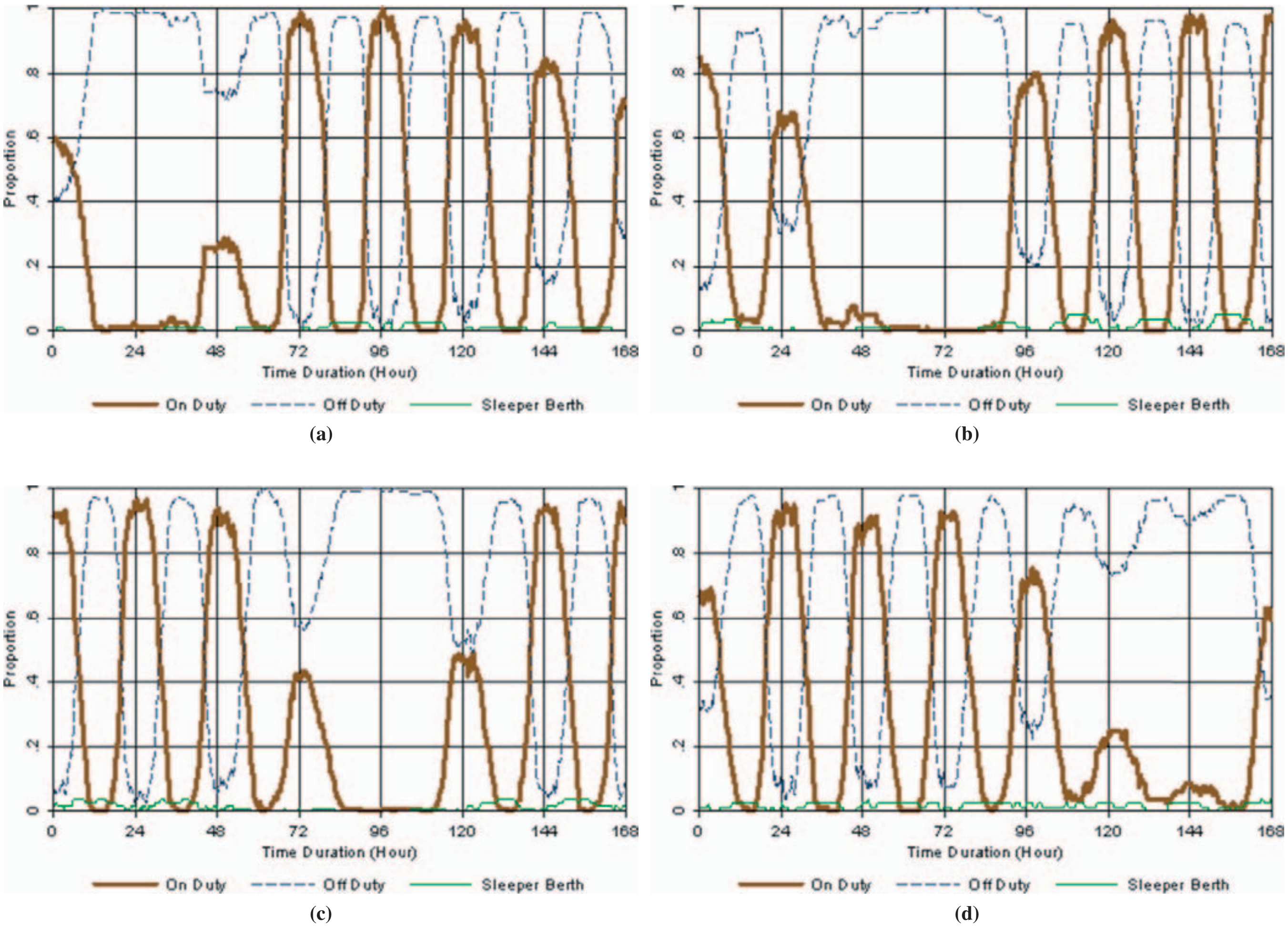

FIGURE 1 Summary of multiday driving for (*a*) Pattern 1, (*b*) Pattern 2, (*c*) Pattern 3, and (*d*) Pattern 4.

As truckers drive more, the odds from this effect are reduced. This finding will be quantitatively examined with statistical models, in the following section.

Driving Patterns 5 to 10 are summarized graphically in Figure 2.

- Pattern 5 has regular work scheduled during days 1 to 3, but working hours drop during day 4, with very few drivers working on days 5 and 6. Drivers are increasingly working through day 7 after about noon, but only 40% of drivers work at that time (40% are off duty, and 20% are in a sleeper berth). Off duty and use of sleeper berth vary in days 1 to 4, showing an irregular on-duty schedule. Drivers return to work at night after having several days off, similar to Pattern 4. This pattern has a relative risk of 0.94.
- Pattern 6 has the lowest relative risk of the 10 patterns (0.52). Drivers in this pattern are on duty infrequently during days 1 to 4, increasing their on-duty time during days 5, 6, and 7. On-duty time builds gradually from noon and peaks at night around 10 p.m. About 20% of drivers in this pattern use sleeper berths, particularly during days 5 to 7. In contrast to Pattern 1 and many other patterns, this pattern is relatively irregular: 60% to 80% of the drivers are off duty on days 1 to 4.
- Pattern 7 has somewhat irregular driving on days 1 to 4 with relatively few drivers on duty. Days 5 to 7 show most drivers scheduled with starting time in the morning, peaking at about 6 a.m. and ending in late afternoon, around 4 p.m. to 6 p.m. Sleeper berth use is low during days 1 to 4 but picks up to about 20% of drivers on days 5 to 7. The relative risk for this group is 0.69.
- Pattern 8 consists primarily of daytime work, starting around 6 a.m., building to a peak at noon, and then dropping off to no drivers working from about 10 p.m. through 2 a.m. The pattern is regular on days 1, 2, 3, and 7, and about 50% of the drivers work on day 4. Most drivers are off duty on days 5 and 6, and there is almost no use of sleeper berth. This pattern has a relative risk of 0.84.
- Pattern 9 is a rather mixed pattern; there is little work on day 1, but about 50% of the drivers in the pattern are working on day 2 clustered around 2 p.m. On days 3 to 5, drivers are scheduled regularly around 2 p.m., ending their shifts in the early morning. About 30% to 40% of drivers work on days 6 and 7, centered on 2 p.m. This pattern has a relative risk of 0.79.
- Pattern 10 has regular work centered at noon, particularly for days 1, 5, 6, and 7. About 50% of the drivers work on days 2 and 4, and almost all are off duty on day 3. This pattern is similar to Patterns 8 and 9, involving primarily daytime driving centered on noon. The difference is when during the 7-day period the off-duty time is captured. This pattern has among the lowest relative risks, at 0.56.

The patterns and their associated relative risk treat crash probabilities as if they depended on only one variable. A complete

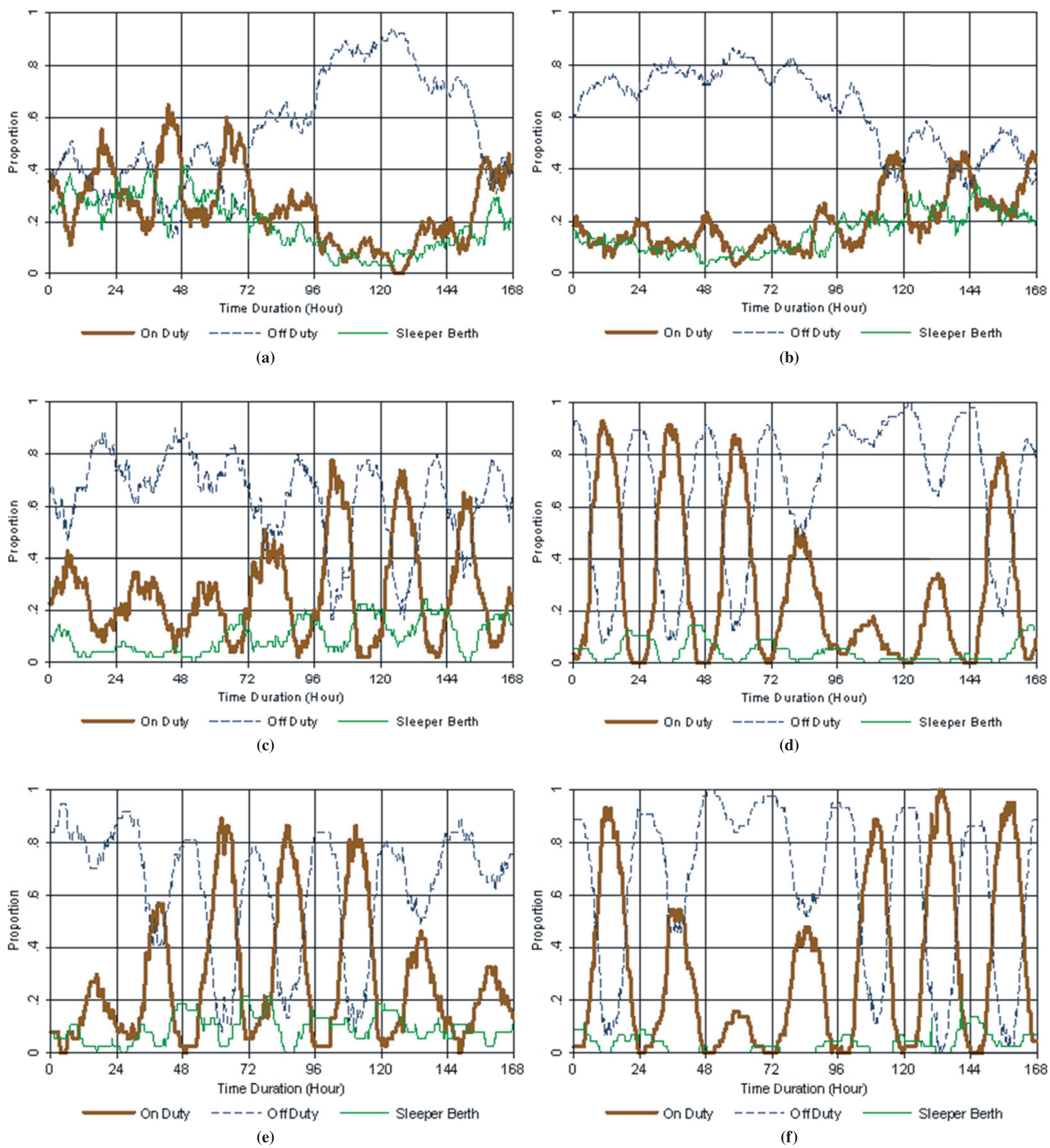

FIGURE 2 Summary of multiday driving for (*a*) Pattern 5, (*b*) Pattern 6, (*c*) Pattern 7, (*d*) Pattern 8, (*e*) Pattern 9, and (*f*) Pattern 10.

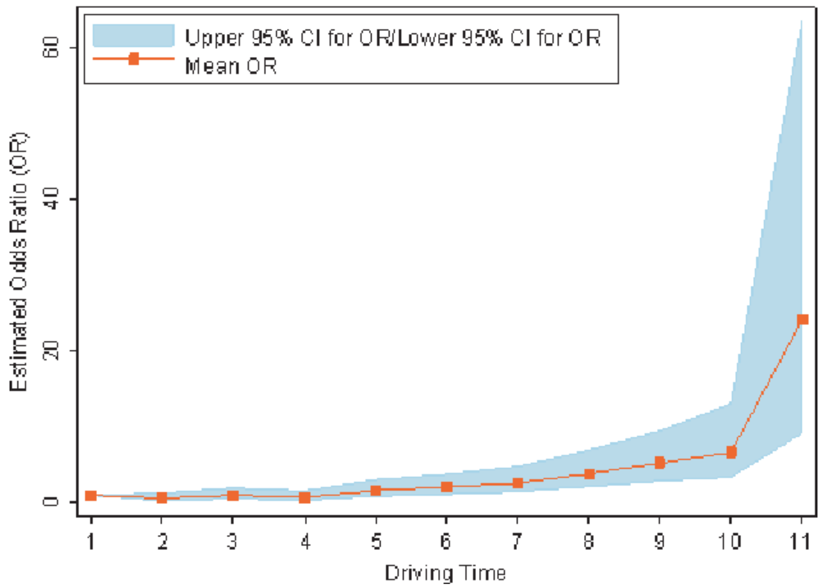

FIGURE 3 Trend in crash odds with hours driving (CI = confidence interval; OR = odds ratio).

understanding of crash odds is obtained through the use of the survival formulation with multiple predictor variables.

Discrete-Time Survival Models

Logistic regression models were estimated in the following sequence, to determine the interaction between the predictor variables:

- Driving time only (Figure 3 and Table 3).
- Driving time and driving pattern.
- Estimating a series of models exploring interactions between driving time and pattern. For each driving hour, a model was estimated with interaction terms with driving patterns. This resulted in a series of 10 additional models, each yielding a set of driving hour–driving pattern interactions. A significance level of 0.20 was used in this screening, to not eliminate potentially important interactions. After 10 initial models were estimated, the interaction terms identified in the 10 models were all added into one model, and they were gradually extracted one at a time to derive a final set of final interaction terms. This approach was successfully used in a previous paper (*8, 17*) and allowed the testing of many interactions despite limited sample size.
- Exploring the effect of driving breaks. This is a comparison of no break during a trip compared with one, two, and three or more breaks. A break is defined as any time off duty or in a sleeper berth of at least 15 min to a maximum of 1.5 h during a driving period.
- Exploring the presence of a 34-h recovery period, defined as the presence of 34 or more h consecutively off duty. Models compared the presence of the recovery and time of day when drivers return to work (either day or night).

The Akaike information criterion (AIC) is a measure of the relative goodness of fit of a statistical model while adjusting for the number of parameters in the model. For the final model, the AIC is

TABLE 3 Crash Odds as Function of Driving Time

Coefficient	Estimate	Standard Error	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
Intercept	–3.555	0.233	<2E–16	na	na	na
2nd hour (1 to 2 h of driving)	–0.511	0.383	.182	0.600	0.283	1.270
3rd hour (2 to 3 h of driving)	–0.008	0.339	.980	0.992	0.511	1.926
4th hour (3 to 4 h of driving)	–0.286	0.373	.444	0.751	0.362	1.561
5th hour (4 to 5 h of driving)	0.486	0.316	.123	1.626	0.876	3.019
6th hour (5 to 6 h of driving)	0.722	0.311	.020	2.059	1.120	3.785
7th hour (6 to 7 h of driving)	0.974	0.304	.001	2.649	1.459	4.808
8th hour (7 to 8 h of driving)	1.351	0.298	.000	3.862	2.153	6.927
9th hour (8 to 9 h of driving)	1.655	0.306	.000	5.232	2.871	9.535
10th hour (9 to 10 h of driving)	1.895	0.342	.000	6.650	3.404	12.992
11th hour (10 to 11 h of driving)	3.188	0.492	.000	24.231	9.236	63.571

NOTE: na = not applicable.

1,644.3, an improvement from the driving time only model, 1,678.5. Therefore, only the driving time and final models are presented and discussed. Additional detail is available in the technical report (*17*). The final model including all predictors is summarized in Table 4.

Crash Odds as Function of Driving Time

Table 3 summarizes the results of the model estimating the probability of having a crash at time *t*, given survival until that time. Using the first hour as the baseline, one sees that there is an inability to detect a driving time effect for hours 3 and 4. The second hour is marginally lower than the first ($p = 0.18$). After the 4th hour, there is an increase in crash odds with hours driving. The effect in the 5th hour is barely significant compared with hour 1 ($p = 0.12$), but it shows an increase in the crash odds of 63%, that is, the odds ratio in column 5 of the table is 1.626, indicating an increase in crash odds compared with the baseline (100) of 63%. Hours 6 to 11 show increases in the odds ratio, with each hour greater than the previous hour. These results are consistent with those of previous studies of less-than-truckload carriers conducted with data from the 1980s (*8–10*).

The trend in crash odds ratios is summarized graphically in Figure 3, using the odds ratios from column 5 of Table 3. The gray band in Figure 3 indicates that the confidence interval increases with driving time as well (reflecting reduction in sample size as hours driving increase from 1 to 11). The goodness of fit using the AIC criteria is 1,678.5, which will be a baseline measure used to assess the value of adding variables to the logistic regression.

TABLE 4 Crash Odds as Function of Driving Time, Pattern, Interactions, Driving Breaks, and Interactions of 34-h Recovery Period and Time-of-Day-of-Return

Coefficient	Estimate	Standard Error	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
Intercept	–3.445	0.368	<2E–16	na	na	na
2nd hour (1 to 2 h of driving)	–0.791	0.426	.064	0.454	0.197	1.046
3rd hour (2 to 3 h of driving)	0.013	0.340	.970	1.013	0.520	1.971
4th hour (3 to 4 h of driving)	–0.250	0.374	.505	0.779	0.374	1.623
5th hour (4 to 5 h of driving)	0.557	0.318	.080	1.745	0.936	3.252
6th hour (5 to 6 h of driving)	0.572	0.351	.103	1.772	0.891	3.526
7th hour (6 to 7 h of driving)	0.929	0.325	.004	2.531	1.339	4.784
8th hour (7 to 8 h of driving)	1.484	0.302	.000	4.411	2.440	7.976
9th hour (8 to 9 h of driving)	1.833	0.312	.000	6.252	3.391	11.526
10th hour (9 to 10 h of driving)	1.962	0.378	.000	7.114	3.391	14.925
11th hour (10 to 11 h of driving)	3.540	0.510	.000	34.471	12.681	93.701
Pattern 1	–1.151	0.335	.001	0.316	0.164	0.609
Pattern 2	–0.717	0.331	.030	0.488	0.255	0.934
Pattern 3	–0.336	0.299	.261	0.715	0.398	1.284
Pattern 5	0.021	0.302	.946	1.021	0.564	1.846
Pattern 6	–0.866	0.370	.019	0.421	0.204	0.868
Pattern 7	–0.567	0.354	.109	0.567	0.283	1.135
Pattern 8	–0.263	0.336	.434	0.769	0.398	1.486
Pattern 9	–0.945	0.426	.027	0.389	0.169	0.896
Pattern 10	–0.962	0.410	.019	0.382	0.171	0.854
Drivers took one break (off-duty or sleeper berth) during a trip	–0.169	0.162	.296	0.845	0.615	1.160
Drivers took two breaks (off-duty or sleeper berth) during a trip	–0.719	0.280	.010	0.487	0.282	0.843
Drivers took three or more breaks (off-duty or sleeper berth) during a trip	–0.089	0.111	.422	0.915	0.736	1.137
7th hour and Pattern 6	1.366	0.578	.018	3.920	1.262	12.172
10th hour and Pattern 4	1.567	0.774	.043	4.793	1.052	21.842
6th hour and Pattern 3	1.079	0.489	.027	2.941	1.127	7.671
2nd hour and Pattern 9	2.301	0.784	.003	9.983	2.148	46.400
Recovery period immediately before a trip starting at nighttime	0.458	0.281	.103	1.581	0.911	2.743
Recovery period immediately before a trip starting at daytime	0.926	0.292	.002	2.523	1.424	4.473
Trip starting at nighttime without a recovery period immediately before the trip	0.561	0.217	.010	1.753	1.146	2.681

NOTE: na = not applicable.

Some may ask if any particular driving hour is significantly different from any other hour (rather than focus on comparisons with the first hour only). A comparison of any driving time parameter with any other driving time parameter has been conducted with a Wald test (*20–22*). The null hypothesis for the test is that the difference in the two parameter values is equal to zero, compared with a difference that is different from zero. The test was unable to detect a difference between hours 1 to 4 (except for some marginally significant differences with respect to the drop in crash odds in hour 2). In general, for hours 5 to 11, the crash odds ratio was different in all comparisons, except those in immediately adjacent driving hours (e.g., 6 compared with 5 and 7; 8 compared with 7 and 9). These comparisons had p-values that varied from .16 to .45. The authors believe that this variation relates to sample size limitations, not an actual leveling of crash probabilities. Details of these comparisons are shown in Jovanis et al. (*17*).

Crash Odds as Function of Driving Time, Multiday Driving Pattern, Driving Break, and 34-h Recovery Period

The final model includes the following predictor variables: driving time, multiday driving pattern, driving breaks, and 34-h recovery period (see Table 4). Comparison of the odds ratios for driving time in Tables 3 and 4 indicates that the odds ratios continue to increase with driving time, even when controlling for multiday driving patterns, driving breaks, and time of day with respect to recovery period. The magnitude and statistical significance of estimated coefficients for driving time remain similar to the driving time only model.

The odds ratios for the driving patterns generally tracked the computation of relative risk in Table 2. Pattern 4 (baseline) and Pattern 5 have odds ratios of 1.0. All other patterns have odds ratios indicating reduced crash probability: Patterns 1, 2, 6, 7, 9, and 10 all show significant or marginally significant reductions on crash odds. These multiday patterns include regular night driving (Patterns 1 and 2) and regular day driving (Patterns 7, 9 and 10). Thus, assessment of time of day is more than a simple statement about one time being better than another. Patterns 5 and 8 have parameters unable to be differentiated from Pattern 4 (odds ratio of 1.0). Examination of the odds ratios for Patterns 1 to 4 verifies the qualitative findings from Table 2. Night driving shows a reduction in crash odds for all but Pattern 4: those who return to work after the recovery period and return to a night driving schedule. A series of Wald tests (similar to those conducted for Table 3) were conducted to test for differences in odds ratios among Patterns 1 to 4. In general, the tests support the interpretation that drivers adapt to the return to work from a recovery period, but the most risky part of the return is the first day, particularly for regular night drivers. These findings are based on the multiday patterns only; the effect of the recovery period is modeled with an additional variable.

There is an interest in better understanding the effect, on the probability of a crash, of breaks during driving. While one would be tempted to refer to these as rest breaks, it is not possible to determine rest from the available driver log data. Therefore, this study chooses the term driving break because it represents a cessation in the driving task for a relative short period of time. The variable used to describe the driving break is derived by combining off-duty and sleeper-berth time during the trip of interest. Categorical covariates are used to quantify the influence of different numbers of breaks on each group on drivers. Group One has drivers with no breaks (baseline); Group Two has those taking one break; Group Three has those taking two breaks; and Group Four has those taking three or more breaks. All the breaks result in estimated reductions in crash odds, but the taking of only two breaks results in statistical significance and a 50% reduction in crash odds relative to no driving break.

A series of interaction terms have been created and tested for driving time and driving pattern (two-way interactions only). The significant interactions were retained, and after all driving hours were tested, the interactions were then entered into a common model. Insignificant interactions were dropped, leaving the four significant interactions in Table 4. Four patterns are affected and with different lengths of driving time. However, a few observations can be made about the interactions. The first and third listed interactions result in increases in crash risk for driving in the early morning (near 6 a.m.), a time of low circadian activity. The second interaction term (between hour 10 and Pattern 4) results in driving in later morning; vehicular traffic levels may be high in some areas due to midday travel. The last interaction term results in higher crash odds when driving near 4 p.m. to 5 p.m.; this is another possible time of increased traffic or low circadian rhythms, or both, for some. So the interaction terms in this model do not seem to adjust for the effect of extended time on task; they instead seem to pick up possible circadian or traffic-related effects.

Finally, this study combines two issues concerning recovery periods. What is the effect, if any, of the recovery period? Is there a differential effect for a return to work at night? Recovery period is defined as a period of time consecutively off duty, or off duty in combination with use of sleeper berth, in which at least 34 h elapse. The model formulation has a baseline of no recovery and a daytime trip. Dummy variables represent a 34-h recovery with a night return to duty, a 34-h recovery with a day return to duty, and a night trip without a recovery. The parameter values for the new interaction terms indicate increased odds for all three dummy variables, but particularly for drivers returning during the day.

SUMMARY AND CONCLUSIONS

Both qualitative and quantitative analyses of commercial motor vehicle driver hours of service were conducted during this research to assess the implications of particular hours of service policies on the odds of a crash. The outcome studied was a reportable crash (i.e., crash involved a fatality, an injury requiring medical treatment away from the scene of the crash, or a tow away) that was reported by the trucking companies cooperating with the study. Carrier-supplied driver logs for 7 days before each crash were used and compared with a random sample (two drivers) of drivers not involved in a crash and selected from the same company, terminal, and month. Data were collected from a total of 668 less-than-truckload drivers (224 crash-involved and 462 controls) who were on the road in 2004 to 2005 and in 2010. Statistical tests across the two sets of years failed to show any systematic differences in the data sets, which would preclude their consolidation.

This study explored associations between changes in crash odds ratios (i.e., the probability of having a crash with a given value of a predictor compared with a baseline condition) and the presence of a range of driving-related predictors, including hours driving, driving patterns over multiple days, time of day, breaks during driving, and the 34-h recovery policy.

Key findings of the research are as follows:

- Driving time was consistently associated with increased crash odds: after the fourth hour of driving, crash odds increased for each hour driven. The highest odds are in the 11th hour. The increase in crash odds with time-on-task argues for consideration of a reduction in maximum driving time from 11 to 10 h.

- Multiday driving patterns showed that night driving had reduced crash odds, except when drivers first return from a recovery period (see discussion of Figure 1 and Table 4). The team understands that every driver has to return from a recovery period at some time. The challenge is to seek countermeasures to minimize risks posed by that initial return to work.
- Several analyses were conducted concerning breaks from the driving task [defined as a period within a driving trip when the driver was off duty or within a sleeper berth (typically 15 min to 1 h)]. All driving breaks resulted in reductions in crash odds; the odds of a crash were reduced by 51% for two breaks taken.
- Studies were also conducted of the 34-h recovery period, defined as a period of time consecutively off duty, or off duty in combination with use of sleeper berth, in which at least 34 h elapse. The team explored associations between changes in crash odds ratios (i.e., the probability of having a crash with a given value of a predictor compared with a baseline condition) and the presence of the recovery period with respect to the crash event day and time of day. All the comparisons of the 34-h recovery were for a trip starting immediately after a period of at least 34 h off duty compared with a baseline trip (starting at night or day) without the 34 h off duty. All tests of the 34-h recovery showed an increase in crash odds (significant or barely significant) compared with a baseline of starting a trip without the 34 h off duty. The increased crash odds in the quantitative models were corroborated by comparison of driving patterns and relative risk. Multiday driving patterns with the higher crash relative risk consistently, but not exclusively, involved drivers returning from extended periods off duty. As formulated, the effect of recovery is in addition to the effect of multiday driving.

Taken as a whole, these analyses support the reduction of driving time from 11 to 10 h and the implementation of required driving breaks for drivers. These recommendations are based on crash analyses only; the economic benefits possibly associated with longer driving times and lack of rest breaks should be considered as part of any policy decision.

Methodologically, it would be desirable to include testing a more sophisticated driving break model that includes both length of break and frequency during the day of interest. Such testing awaits additional data to enhance the sample size of observations.

Last, the findings in this paper are for only less-than-truckload data. Additional and somewhat different results are obtained for truckload carriers (*17*).

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