Hours of Service and Driver Fatigue: Driver Characteristics Research

U.S. Department of Transportation
Federal Motor Carrier Safety Administration

May 2011

FOREWORD

Trucks occupy a large and growing segment of the traffic on American highways. On many rural interstate highways, trucks constitute more than one-third of the total traffic stream. Truck crashes present unique safety challenges, including greater mass of the truck and truck drivers' unique working schedules.

It is generally accepted that commercial motor vehicle driver safety is related to drivers' work schedules, including driving time, on-duty/not-driving time, and off-duty time. In 1938, the now-abolished Interstate Commerce Commission (ICC) enforced the first hours-of-service (HOS) rules for the industry to promote the healthy development of the carrier industry and protect drivers' safety.

In this study, qualitative and quantitative analyses of driver hours of service were performed to assess the implications of particular policies on the odds of a crash. The outcomes studied were crashes reported by the trucking companies cooperating with the study. These crashes involved either a fatality, an injury requiring medical treatment away from the scene of the crash, or a towaway. Carrier-supplied driver logs for periods of 1–2 weeks prior to the crash were used and compared to a random sample (two drivers) of non-crash-involved drivers selected from the same company, terminal, and month using a case-control logistic regression formulation. This is the methodology identified in the study proposal and has been used by the study team in many previous research studies. Data were separated into truckload (TL) and less-than-truckload (LTL) analyses because previous research indicated differences in crash contributing factors for these two segments of the trucking industry.

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16. Abstract

There is a need to quantitatively and qualitatively associate crash occurrence with a range of commercial truck driver characteristics, including hours of driving and hours worked over multiple days. The need arises because of the desire to continue to refine Federal hours-of-service (HOS) regulations for truck drivers. An additional factor is the inconsistent and sometimes contradictory findings of truck driver safety research. This research used the probability of a crash after a certain amount of time driving given no crashes until that time. Carrier-supplied driver logs for periods of 1–2 weeks prior to each crash were used and compared to a random sample (two drivers) of non-crash-involved drivers selected from the same company, terminal, and month using a case-control logistic regression formulation. Data were separated into truckload (TL) and less-than-truckload (LTL) analyses because previous research indicated differences in crash contributing factors for these two segments of the trucking industry. Considering all the data, there is a consistent increase in crash odds as driving time increases. LTL drivers experienced increased crash odds after the 6th hour of driving. Breaks from driving reduced crash odds. In particular, a second break reduced crash odds by 32 percent for TL drivers and 51 percent for LTL drivers. There was, however, an increase in crash odds associated with the return to work after a recovery period of 34 hours or more.

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SI* (MODERN METRIC) CONVERSION FACTORS

Table of APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	Millimeters	mm
ft	feet	0.305	Meters	m
yd	yards	0.914	Meters	m
mi	miles	1.61	Kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yards	0.836	square meters	m^2
ac	acres	0.405	Hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME	1000 L shall be shown in m^3	
fl oz	fluid ounces	29.57	Milliliters	mL
gal	gallons	3.785	Liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		MASS		
oz	ounces	28.35	Grams	g
lb	pounds	0.454	Kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or “metric ton”)	Mg (or “t”)
		TEMPERATURE	Temperature is in exact degrees	
°F	Fahrenheit	5 × (F-32) ÷ 9 or (F-32) ÷ 1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	Lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		Force and Pressure or Stress		
lbf	poundforce	4.45	Newtons	N
lbf/in^2	poundforce per square inch	6.89	Kilopascals	kPa

Table of APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
Mm	millimeters	0.039	inches	in
M	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or “t”)	megagrams (or “metric ton”)	1.103	short tons (2000 lb)	T
		TEMPERATURE	Temperature is in exact degrees	
°C	Celsius	1.8c + 32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		Force & Pressure Or Stress		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

* SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003, Section 508-accessible version September 2009).

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ABBREVIATIONS, ACRONYMS, AND SYMBOLS

Acronym	**Definition**
AIC	Akaike Information Criterion
ATRI	American Transportation Research Institute
CI	confidence interval
FMCSA	Federal Motor Carrier Safety Administration
HOS	hours of service
ICC	Interstate Commerce Commission
km	kilometer
OR	odds ratio
LTL	less than truckload
RR	relative risk
TL	truckload
USDOT	U.S. Department of Transportation

See the FHWA Terminology and Acronyms supplement for a list of preferred acronyms.

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EXECUTIVE SUMMARY

In this study, qualitative and quantitative analyses of commercial motor vehicle driver hours of service were performed to assess the implications of particular policies on the odds of a crash. The outcomes studied were crashes reported by the trucking companies cooperating with the study. These crashes involved either a fatality, an injury requiring medical treatment away from the scene of the crash, or a towaway. Carrier-supplied driver logs for periods of 1–2 weeks prior to the crash were used and compared to a random sample (two drivers) of non-crash-involved drivers selected from the same company, terminal, and month using a case-control logistic regression formulation. Data from 2004–05 and 2010 were collected from a total of 1,564 drivers. This is the methodology identified in the study proposal and has been used by the team in many previous research studies (Jovanis et al., 1991; Kaneko and Jovanis, 1992; Lin et al., 1993; Lin et al., 1994).

Data were separated into truckload (TL) and less-than-truckload (LTL) analyses because previous research indicated differences in crash contributing factors for these two segments of the trucking industry. TL carriers typically move goods for an individual firm to another firm, normally loading dock to loading dock and LTL carriers typically move goods over the road for several shippers on the same truck between trucking company-owned terminals. In total, 878 drivers (318 crash-involved and 560 controls) were analyzed in TL operations and 686 drivers (224 crash-involved and 462 controls) were analyzed in LTL operations.

Statistical tests were performed to determine whether it is appropriate to combine the data from 2004–05 and 2010. The study team was concerned that there might be differences in the factors contributing to crashes since 5–6 years elapsed between the data collection periods. A series of Chow tests (Greene, 2003) were performed comparing the two datasets. These tests indicate that there is limited evidence to support the position that the two sets of data are drawn from datasets with different underlying crash associations. The study team reached this conclusion because only the first Chow test, the one with driving time only as a predictor, rejected the null hypothesis. When additional predictors were added, there was 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 datasets across 2004–05 and 2010.

The study 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 to a baseline condition) and the presence of a range of driving-related predictors, including cumulative hours driving, driving patterns over multiple days, time of day, breaks during driving, and the 34-hour recovery policy.

Findings of the research include:

- Driving time and driving patterns over multiple days:
  - Driving time was substantially associated with crash odds in the LTL analysis.
  - Analysis of LTL data shows a strong and consistent pattern of increases in crash odds as driving time increases. The highest odds are in the 11th hour. There is a consistent increase after the 5th hour through the 11th hour. Specifically, the increase in odds is statistically significant in the 6th hour. The crash odds are significantly higher here

than all previous hours, except the 5th. The 7th hour is significantly higher than first 5, but not the 6th; the 8th hour is significantly higher than hours 1–6 and barely higher than the 7th hour; the 9th hour is higher than hours 1–7 and not higher than the 8th hour; the 10th hour is higher than hours 1–8 and not higher than hour 9; and the 11th hour is higher than all previous hours. In this study, the term "barely significant" is used in reference to a predictor variable that does not reach significance in a hypothesis test compared to zero at conventional levels of significance. In order to avoid eliminating predictors that may be important to safety, the study team used a significance probability of 0.20.

  - Use of interaction terms in the TL models revealed associations between some multiday driving patterns and increased crash risk with driving times in the 7–11-hour range. TL drivers who drive during the day have increased odds of a crash with long driving hours. These longer hours mean the drivers may be on the road in the late afternoon and early evening when higher traffic levels are possible.

- Driving breaks were considered as anytime during a driving period when a driver went from driving status to either in-a-sleeper-berth status or off-duty status. When these events occurred during a trip, the odds of a crash were reduced for both TL and LTL drivers (by 32 percent and 51 percent respectively for two breaks).

- Studies were also conducted of the 34-hour recovery period. This is defined as a period of time consecutively off duty, or off duty in combination with sleeper berth use, in which at least 34 hours elapses. As used in this report, it does not imply that cumulative driving hours were restarted to zero thereafter. The study 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 to 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-hour recovery were for a trip starting immediately after being off duty for at least 34 hours compared to a baseline trip (starting at night or day) without the 34 hours off duty. All tests of the 34-hour recovery showed an increase in crash odds (significant or barely significant) for both TL and LTL drivers compared to the baseline of starting a trip without the 34 hours off duty.
  - The increased crash odds in the quantitative models were corroborated by comparison of driving patterns and relative risk for both the TL and LTL analyses. Multiday driving patterns with the higher crash relative risk consistently, but not exclusively, involved drivers returning from extended periods off duty.
  - More detailed models were constructed to compare the joint effects of the 34-hour recovery and driving at night or during the day:
    - Starting a trip during the day without a recovery had the lowest odds of a crash.
    - Starting a trip at night with a 34-hour recovery resulted in a 58–64-percent increase in crash odds compared to a daytime trip without the recovery.
    - LTL drivers experienced a 150-percent increase in the odds of a crash when using a 34-hour recovery and returning to work during the day compared to the no-recovery daytime return to work.

- Targeted analyses of the 34-hour restart policy using a subset of the data from 2010 showed that the occurrence of a “pseudo-violation” over 2 days is associated with an increase in the odds of a crash. Here a “pseudo-violation” is defined as hours driving and working that would have violated the 70-hours-in-8-days rule, had the 34-hour restart not been in effect. This increase in crash odds was not apparent when the extended work allowed by the restart occurred over 1 day only. In fact, there was some evidence of a reduction in crash odds in this situation. Care is needed in interpreting this finding too broadly as the analysis included crash-involved drivers only for one carrier over a limited time period. The case-control application used in the restart analysis does not have the record of success of the method applied more generally in Section 4. More testing is recommended.

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1. INTRODUCTION

1.1 BACKGROUND

Trucks are a vital component of the U.S. economy. That contribution comes from moving raw and finished products, as well as some bulk goods, long distances. Because of the long distances and long driving times involved in these contributions to our economy, driver hours of service (HOS) have been regulated for more than 70 years.

Research on the safety implications of truck driver work hours were investigated in pioneering research during the 1970s (e.g., Harris and Mackie, 1972; Mackie and Miller, 1978). While the studies in the 1970s used crash and other operations data from carriers in addition to some alertness and driving indicators, a major field study was undertaken in the 1990s, which involved drivers who drove regular routes for their firms while also taking a variety of alertness tests and being subjected to measures of driving performance other than crashes (e.g., Wylie et al., 1996).

Throughout the 1990s, the lead author of this study published a series of papers analyzing crash and non-crash data from a large, national-scale less-than-truckload (LTL) carrier (Jovanis and Chang, 1990; Chang and Jovanis, 1990; Jovanis, Kaneko and Lin, 1992; Kaneko and Jovanis, 1992; Lin, Jovanis and Yang, 1993; Lin, Jovanis and Yang, 1994). A subsequent paper (Park, Mukherjee, Gross and Jovanis, 2005) compared findings from an analysis of the crash dataset from the 1980s and the experimental data collected by Wylie et al. (1996). Campbell conducted a study of fatigue and crash odds using fatal crash data from 1991–2002 (Campbell, 2005).

One of the challenges of conducting research in truck safety and HOS is that various studies have found differing effects of driving hours. Several studies using crash data from a variety of sources have found increased crash odds (or relative risk) with hours driving, particularly after about 5–6 hours. Increased crash odds were found by: Jovanis and colleagues; Campbell and Hwang; Harris and Mackie; and Mackie and Miller. Studies by Frith (1994) and Saccomanno (1995) also found association between driving hours and increase crash odds.

By contrast, the Wylie et al. (1996) study, using alertness tests and instrumented truck measures rather than crashes, found a stronger correlation between fatigue and time of day, and very little correlation between fatigue and driving hours. Many other researchers have also found elevated crash odds with night and early morning driving including Mackie and Miller (1978); Hertz (1988); Kaneko and Jovanis (1992); and Kecklund and Akerstedt (1995). In another study, Klauer et al. (2003) conducted an experiment with 30 solo drivers and 13 team drivers with data measured by both objective and subjective measures. They found team drivers had extreme fatigue only in the morning and night hours and solo drivers had fatigue incidents throughout the day and night, with fewer fatigue incidents in the morning and more in the evening and nighttime.

The Federal Motor Carrier Safety Administration (FMCSA) changed the truck driver HOS rule in 2003. In the new rule, the FMCSA extended driving time from 10 to 11 hours, reduced the maximum consecutive on-duty time to 14 hours, and mandated that the time run continuously from the time the driver started on duty (i.e., off-duty time cannot extend the 14-hour period). The minimum time off duty between driving periods was also increased from 8 to 10 hours. Maximum on-duty times over 7/8 days were retained as 60/70 hours, but a driver was now allowed to restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty.

The objective of this report is to study the effect of the new HOS rules on road safety using crash data. The focus is on the effects, if any, of aspects of the HOS rule that changed in 2003, particularly maximum driving time after 10 hours or more off duty. In addition, other aspects of driving that are known to be associated with crashes, such as time of day and driving patterns over multiple days, were explicitly included in the study.

1.2 STRUCTURE OF THE REPORT

Section 2 describes the data used in the study. The statistical framework for the study is described in Section 3, including a description of the logistic regression models and the application of cluster analysis to the development of multiday driving patterns. Section 4 describes the application of the statistical methods to the data at hand. Appendix A contains additional analyses supporting the research but not needed in the body of the report.

2. THE DATA

The acquisition of data for the study followed a method similar to one used in previous studies (e.g., Lin et al., 1993; Jovanis et al., 2005; Park et al., 2005). Carriers were contacted requesting their cooperation in the study. From the carriers, the study team requested a list of crash information along with details of the hours driving prior to the crash. The requested HOS data for crash-involved drivers included their status in one of four categories: driving, on duty/not driving, off duty, and in a sleeper berth. These data were requested from electronic onboard recorders (EOBR) or paper driver logs, whichever was available. In order to conform to the requirements of the contract, the data needed to be available at 15-minute intervals for 7–14 days prior to the occurrence of the crash. In addition, comparable data were requested for non-crash drivers working for the same firm and dispatched from the same terminal during the same month as the crash-involved driver. For the non-crash data, a driver was first selected from the same terminal, then the driving records were extracted—again for 7–14 days. The study team randomly selected the individual trip to be compared statistically with the crash trip.

The study team recognizes the challenges in obtaining information of this type from carriers. It is an imposition on the carriers to supply the data, particularly in an economic environment that is intensely competitive. In response, the study team offered to work with paper driver logs, coding the data for computer analysis from paper records. Several carriers opted for this data-sharing method, while others were able to provide computer-readable spreadsheet records which were checked for errors and then used directly in the analysis. In all cases, data were checked for obvious coding errors (e.g., a driver being off duty at the time a crash was reported to have occurred) and any differences were resolved. Some data provided by carriers contained partial records of driving (e.g., perhaps only 3 days rather than the requested 7–14). In these circumstances a request was made to provide complete data, but if the complete data were not available, the observation was dropped from the dataset.

The core steps of the method are the same as those used in previous studies: the crash day is used as the starting point to develop additional data that can be associated with the crash event. Driver logs are obtained for prior days (in this case, 2 weeks if possible) and a random sample of non-crash drivers are selected from the same terminal in the same month (Jovanis et al., 1991; Kaneko and Jovanis, 1992; Lin et al., 1993; Lin et al., 1994).

Figure 1 shows the timeframe used to identify the data used in the study. The crash day appears at the top of the figure with the line representing the 24 hours in the day and the "X" representing the time of day of the crash. Immediately below this line is the representation of a day for a non-crash driver with a "Y" representing the randomly selected trip within that day. These 2 days are the starting point for the analysis and are referred to as the "day of interest" because many variables used in the analysis are referenced with respect to these days. There are two non-crash observations for every crash (initially at least). Therefore, the number of trips like the one designated with the "Y" in Figure 1 are actually twice the number of crashes. Incompleteness in driver logs resulted in the loss of some crash and non-crash data, however, so the 2:1 ratio is not always maintained. All other driving-related variables are derived from this point looking back in time. The inclusion of additional days prior to the day of interest is shown in the second two lines, which depict the addition of 7 days prior to the day of interest. For 2010 data this period was extended to 14 days.

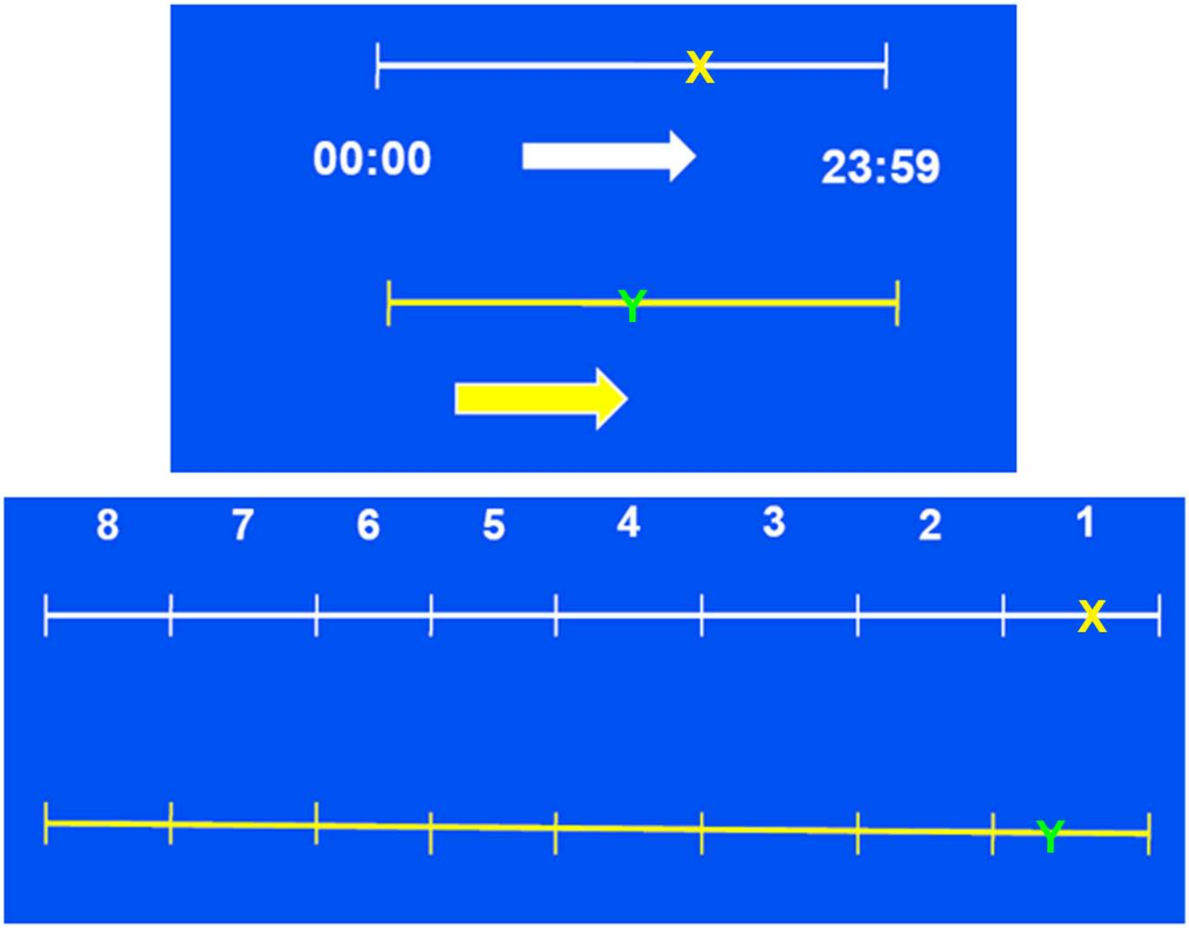

Figure 1. Summary of Method Used for Data Extraction from Carrier-Supplied Driver Logs

Several datasets were merged to form the full dataset for this study. Data from TL and LTL carriers collected in 2004–05 (Jovanis et al., 2005) were combined with additional data from carriers collected in 2010. 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 (see Table 4). While some may argue that carriers may selectively report crashes, it is difficult to see how they could selectively report crashes due to hours of service. Similar arguments could be raised about the non-crash data, but it is difficult to believe that the carriers would be able to manipulate the data to achieve a specific outcome, given the complexity of the statistical methods used. While it is *possible* that manipulation of the data has occurred, the study team believes it is unlikely.

The decision to combine the 2004–05 and 2010 data was made specifically to allow greater precision in the development of the statistical models. Appendix A describes the tests conducted to support the combining of the datasets including summaries of the results of the tests. The analyses conducted, using a Chow test (Greene, 2003), support the combining of the 2004–05 data with the 2010 data in two market segments: TL operations and LTL operations.

Separate analyses are conducted for TL and LTL carriers because previous research (Jovanis et al., 2005; Park and Jovanis, 2011) indicated that the crash odds models for the two carrier types are significantly different. The TL carrier typically fills the truck with a full load from one consignee and moves the shipment from a producer to a user, typically from the loading dock of one firm to the loading dock of another firm. Routes can vary greatly as can the origin and destination of the trips. As a result, the drivers experience generally more variability in the driving patterns (e.g., time of day, driving time, off-duty time) than drivers operating with LTL carriers. These carriers generally move smaller shipments, with many consignees on the same truck. The classical LTL operation has pick-ups and deliveries handled in smaller units maneuvering in urban spaces. The line-haul driver moves the shipment between company-owned terminals generally located at the junction of interstates and outside of city centers. As a result, the line-haul drivers (those used in this study from the LTL carriers) drive more regularly over multiple days because the origin and destination of their trips are company-owned locations. These classical descriptions fit the preponderance of the services provided by each carrier type in this study.

A Chow test was also conducted to test for differences between TL and LTL crash contributing factors. The initial test with driving time showed a strong difference as do the models described in Section 4. It was clear that separate analyses for each carrier type would yield the greatest insight concerning crash associations.

Table 1 summarizes the sample sizes obtained from each of the five carriers participating in the 2004–05 and 2010 time periods (one carrier provided data for both time periods). While data were collected for two non-crash drivers for each crash-involved driver, it was not possible to retain all records due to missing data at the carrier level (mostly for non-crash drivers). Attempts were made to obtain these data from the carriers, but generally, the data initially received was what was available.

Table 1. Sample Size for TL and LTL Data Analyses

Truckload	**Crash**	**Non-Crash**	**Total**
Firm 1 (2004–05)	79	175	254
Firm 1 (2010)	130	263	393
Firm 2 (2010)	109	122	231
Subtotal	318	560	878
Less-than-Truckload	**Crash**	**Non-Crash**	**Total**
Firm 3 (2004–05)	45	90	135
Firm 4 (2004–05)	79	188	267
Firm 5 (2010)	100	184	284
Subtotal	224	462	686
Total	**542**	**1,022**	**1,564**

Table 2 is a summary of the number of crashes experienced in the aggregate, along with several measures of exposure. The row at the top displays the 11 driving hours. The second row displays the number of crashes experienced in each of the 11 driving hours. The third row contains the number of non-crash-involved drivers on the road in each driving hour. Notice that the row starts with 1,022 drivers on the road in hour 1; this is the same as the number of non-crash drivers shown in the last row of Table 1. As these 1,022 drivers complete their trips, the number exposed in each hour declines. Thus the entries in the third row decline from 1,022 in hour 1 to 1,000 in hour 2 and then 949 in hour 3. The number of non-crash drivers exposed to the risk of a crash continues to decline until hour 11 when the last 50 drivers complete their trip.

At the same time, drivers who eventually have crashes are also exposed to risk during the hours before the crash. This exposure is accounted for in row 4. This row begins with all the crash-involved drivers starting to drive in hour 1. As crashes occur, the number of drivers exposed decreases, until only 16 remain and have a crash in the hour 11.

The 5th row contains the total exposure for each hour, calculated as the sum of the entries in rows 3 and 4. Finally, the last row contains the crash-to-exposure ratio. It is calculated as the number of crashes in each hour from row 2, divided by the total exposure in each hour as contained in row 5. Using all the crash and non-crash data available for modeling, one can see that the crash exposure ratio gradually increases, especially after the 6th hour of driving.

Table 2. Summary of Aggregate Number of Crashes and Exposure to Risk for 11 Driving Hours

Driving Hours	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Number of Crashes	80	52	60	54	53	52	57	55	38	25	16
Number of Non-Crash Drivers Exposed	1,022	1,000	949	888	810	712	620	495	362	190	50
Number of Crash Drivers Exposed	542	462	410	350	296	243	191	134	79	41	16
Total Exposure	1,564	1,462	1,359	1,238	1,106	955	811	629	441	231	66
Crashes/Exposure	0.051	0.036	0.044	0.044	0.045	0.054	0.070	0.087	0.086	0.108	0.242

A summary of the crash occurrence with hours driving is shown in Table 3.

The driving status is recorded for every 15 minutes on the day of the crash, as well as the prior 7 days. Given four 15-minute periods in an hour, 24 hours in a day, and 7 days of interest, this yields 672 indicator variables, separately coded for a driver being on duty/not driving, driving, off duty, and, in a sleeper berth. Different combinations of these variables are used in different analyses in Section 4 of the report. In virtually all cases, the day of the crash and the corresponding non-crash day are referred to as the "day of interest." In addition, the crash trip and the randomly selected non-crash trip are also often referred to as the trip of interest. From these data, several measures of HOS are derived including:

- The pattern of driving over the previous 7 days (prior to the day of interest) are extracted from the data using cluster analysis as described in the next section. The concept is to have the day of interest count as the 8th day and the prior 7 days represent those days corresponding to the 70-hour rule (see Table 3).
- The presence of a 34-hour recovery period is noted and it represents the presence of simply 34 or more consecutive hours off duty. Additional targeted analyses are used to focus on the 34-hour restart policy (using a specific analysis method). Details of these analyses are in described in Section 3. Results are found in Section 4.

- The presence of a break from driving was also identified as a period within a driving trip where the driver was off duty or in the sleeper berth. The minimum time for a driving break was 15 minutes. The study team could not tell whether the driver was "resting" but it seemed clear that there was at least a cessation from driving. These measures were used to test hypotheses about the safety implications of breaks from driving during a particular trip. Separate measures were obtained for one, two, and three or more rest breaks during a trip.
- The time of day of travel during the trip of interest was tested to explore the effect of driving at different times of the day.
- As is common in statistical modeling, a range of interaction terms were explored to examine the effect of driving factors on crash odds.

Table 3. Summary of Crash Data by Hours Driving, Year, and Carrier Type

		dh1	dh2	dh3	dh4	dh5	dh6	dh7	dh8	dh9	dh10	dh11	Row Total
All Data	Number of Crashes	80	52	60	54	53	52	57	55	38	25	16	542
2010	Number of Crashes	51	28	37	37	31	33	34	33	26	18	11	339
2004	Number of Crashes	29	24	23	17	22	19	23	22	12	7	5	203
TL	Number of Crashes	61	39	43	42	30	27	29	23	9	6	9	318
LTL	Number of Crashes	19	13	17	12	23	25	28	32	29	19	7	224

Table 4. U.S. Department of Transportation (USDOT) Hours-of-Service Rules

Property-Carrying Commercial Motor Vehicle Drivers	**Passenger-Carrying Commercial Motor Vehicle Drivers**
11-Hour Driving Limit May drive a maximum of 11 hours after 10 consecutive hours off duty.	**10-Hour Driving Limit** May drive a maximum of 10 hours after 8 consecutive hours off duty.
14-Hour Limit May not drive beyond the 14th consecutive hour after coming on duty following 10 consecutive hours off duty. Off-duty time does not extend the 14-hour period.	**15-Hour On-Duty Limit** May not drive after having been on duty for 15 hours following 8 consecutive hours off duty. Off-duty time is not included in the 15-hour period.
60/70-Hour On-Duty Limit May not drive after 60/70 hours on duty in 7/8 consecutive days. A driver may restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty.	**60/70-Hour On-Duty Limit** May not drive after 60/70 hours on duty in 7/8 consecutive days.
Sleeper Berth Provision Drivers using the sleeper berth provision must take at least 8 consecutive hours in the sleeper berth, plus a separate 2 consecutive hours either in the sleeper berth, off duty, or any combination of the two.	**Sleeper Berth Provision** Drivers using a sleeper berth must take at least 8 hours in the sleeper berth, and may split the sleeper-berth time into two periods, provided neither is less than 2 hours.

USDOT Web site: http://www.fmcsa.dot.gov/rules-regulations/topics/hos/index.htm, accessed 3/27/2011 at 5:30 p.m.

3. METHODOLOGY

3.1 OVERVIEW OF METHODOLOGY

The study of crash odds with hours driving requires the development of a method that can represent the time-dependencies inherent in truck driving. These include:

- The time spent driving and on duty during one duty period (set to a maximum of 11 hours and 14 hours, respectively).
- The cumulative time spent driving and on duty over multiple days (70 hours in 8 days for carriers in this study).
- Time off duty and/or in a sleeper berth.
- The pattern of use and duration of recovery periods.
- The pattern of work over multiple days, including the times of day over each day.
- The pattern of driving times over multiple days.

This section describes how the basic data available from trucking companies are processed to capture the required driving descriptors.

The crash day, or the randomly selected non-crash day, is referred to as the day of interest. All other driving HOS-related variables are derived from this point looking back in time (see Figure 1). The primary tool used to quantitatively assess the safety implications of driver HOS is time-dependent logistic regression, the same tool used in numerous previous studies (e.g., Kaneko and Jovanis, 1992; Lin et al., 1993; Lin et al., 1994, Park et al., 2005).

A series of predictor variables are used with the time-dependent logistic regression model in addition to driving time. The predictors are described in detail in Sections 3.4 through 3.8 and include measures of multiday driving, interaction terms for driving time and multiday driving main effects, time of day, driving breaks, and timing of recovery periods. An overview of how the predictor variables were tested for inclusion in the model is provided in Section 3.2.

In addition to the time-dependent logistic regression, a separate analysis was undertaken concerning the association between the use of the 34-hour restart and crash probability. Analysis of this issue required a different modeling approach than for the study as a whole, because of the complexity of assessing a restart policy. The approach is described in detail in Section 3.9. Finally, time-dependent logistic regression was applied to the dataset as a whole, at the request of the sponsor. The model developed in response to this request is described in Section 3.10.

3.2 OVERVIEW OF MODELING FRAMEWORK

Figure 2 is an overview of the modeling procedure applied in this study. The statistical testing of predictors begins with the inclusion of the 11 driving hours as predictors (Step 1). The survival formulation described in Section 3.3 is used to capture the concept that a crash in a particular hour (e.g., hour 7) implies that the driver *survived* (did not have a crash) for the first 6 hours. This fundamental concept of survival is built into the logistic model. In the second step, the multiday patterns derived from cluster analysis are entered as a group and tested for significance as predictors against a constant term only using a likelihood ratio test. At Step 3, both predictors are entered and the improvement in goodness-of-fit is explored using the Akaike Information Criteria (AIC).

As suggested by a peer reviewer, the model discussions include changes in AIC as well as a discussion about the parameter rationale. This concern recognizes that crashes are rare events, even when applying a case-control approach to data analysis. As such, there should be some allowance for inclusion of variables that do not meet typical levels of significance. This approach is suggested in a paper by Hauer (2004) and has been implemented by using a significance probability of 0.20 for parameter inclusion. In addition, most predictors (with the exception of the interaction terms) are retained in the models in order to better document the contribution of the predictor to model fit. There are strong interests engaged in the discussion of hours of service. The study team believes that a policy of inclusion (especially since experience tells us most of the predictors in use are independent of each other) will result in a clearer understanding of what was, and what was not, found in the study.

Step 4 adds an interaction term for the first driving hour and each of the 10 driving patterns. Steps 5 and 6 are a series of tests of interaction terms for driving time and multiday driving pattern. Because of the number of possible interaction terms to test (11 driving hours by 10 driving patterns) a sequential procedure was adopted (again similar to one used in previous research—Lin et al., 1993). The approach here is to consider the 11 driving hours as interaction terms with one driving pattern at a time. This adds 11 new predictors to each model. The interaction terms are entered at one time. Those failing to reach significance are removed one at a time, carefully monitoring any changes in other parameters in the process. Once all the non-significant interaction terms are removed, those remaining are noted for later testing (Step 5). The next multiday pattern is used as a main effect along with the 11 driving hours (Step 6); this process repeats until all driving hours and patterns are tested. In Step 7, the results of all the previous models are combined and non-significant predictors again removed. At Step 8, the model—with driving time and multiday patterns main effects and interactions—is used to explore additional predictors.

One of the predictors tested was time of day. It is described in Section 3.5, but testing revealed some correlation with the driving pattern/driving time interactions. As a result, the model with time of day is analyzed for TL operations only. No model was estimated for LTL, as the results for TL did not seem to materially add to the understanding of crash risk.

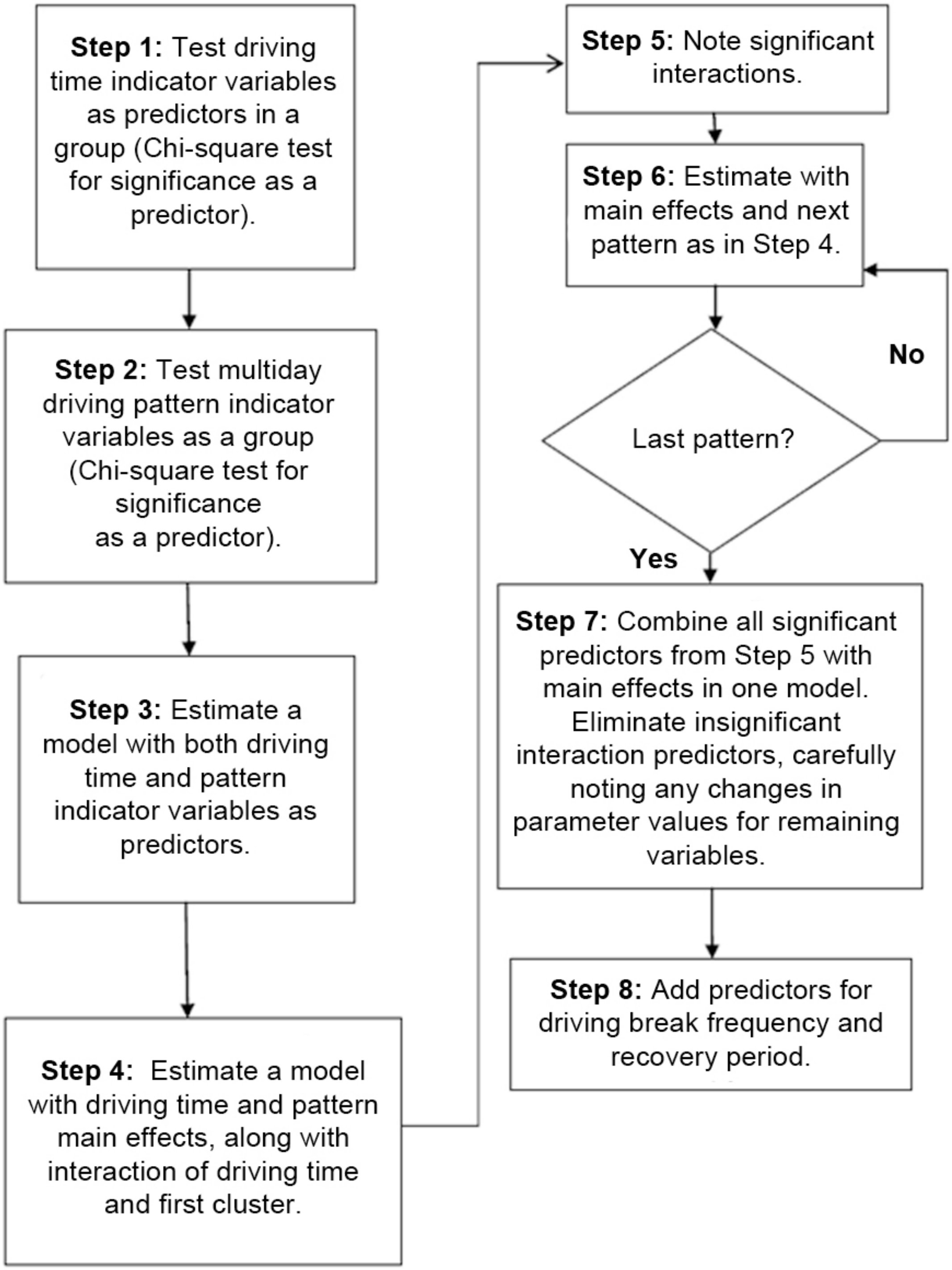

Figure 2. Overview of Modeling Procedure Used in This Research

3.3 MODELING CRASH ODDS

Figure 3 shows a general formulation for the time-dependent logistic regression model (Brown, 1975; Abbott, 1985; Hosmer and Lemeshow, 1989) is:

$$P_{it} = P(Y_{it} = 1 | Y_{it} = 0 \; for \; t' < t, X_i) = \frac{exp[g(X_i, t, \beta)]}{1 + exp[g(X_i, t, \beta)]}$$

$$\text{where } g(X_{ij}, t, \beta) = \Sigma_{j=0}^{r} \beta_j X_{ji} + \Sigma_{k=1}^{T-1} \beta_{r+k} X^*_{ki} + \Sigma_{n=1}^{s-1} \beta_{r+(T-1)+n} X_{ni}(t_i)$$

Figure 3. Equation for the Time-Dependent Logistic Regression Model

The model describes the probability that driver *i* has a crash (*Y*=1) at time *t* given that the driver has no crash ($Y_{it} = 0$) for all *t'* less than *t.* The model thus describes the probability of a crash at a point in time given survival until that time. Here *beta* subscript *j* are the coefficients of the explanatory variables, *t* represents the ability to include time-dependent covariates and *X* subscript *i* subscript *j* are the observation values of driver *i* with the explanatory variable *j*.

The first term of the right-hand side of the second equation represents time-independent explanatory variables. The second term represents the time main effect like driving time, and *X** subscript *k* subscript *i* represents the time interval *k* for driving time. A trip with a length of *k* time intervals would be represented by a series of indicator variable with *X** subscript *k* subscript *i* = 1. The last term represents the time-dependent covariates like multiday driving pattern (Lin, Jovanis, and Yang, 1994). A data replication scheme is needed to represent the survival effect because the binary logistic model provides for only one outcome (Kaneko and Jovanis, 1992).

The data replication method is illustrated in Table 5. For example, if a driver has a crash in the third driving hour, then three rows are used, each representing the driver's status for that hour. During the first and the second hour, row 1 and row 2, the driver does not have a crash, so dependent variable (outcome) is a zero. In the third hour the crash occurs, so the outcome becomes one. If a driver completes the drive in 3 hours without a crash, then all three rows (three observations) have a zero outcome.

Table 5. Coding Driving Hours and Outcomes for Survival Effect

Crash/No Crash	Status	Outcome	Hour T1	Hour T2	Hour T3	Hour T4	Hour T5–T9	Hour T10
Driver 1 has crash	Non-Crash	0	1	0	0	0	0	0
Driver 1 has crash	Non-Crash	0	0	1	0	0	0	0
Driver 1 has crash	Crash	1	0	0	1	0	0	0
Driver 2 has no crash	Non-Crash	0	1	0	0	0	0	0
Driver 2 has no crash	Non-Crash	0	0	1	0	0	0	0
Driver 2 has no crash	Non-Crash	0	0	0	1	0	0	0

3.4 MULTIDAY DRIVING PATTERNS

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 minutes typically reported for each hour of each day, there are a very large number of possible driving patterns over multiple days for each driver. One is then left with 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 (Jovanis et al., 1991; Kaneko and Jovanis, 1992; Lin et al., 1993; Lin et al., 1994) and is employed in this study, as well.

The basic input to the cluster analysis method is the duty status (i.e., driving, on duty/not driving, off duty, sleeper berth) of every driver for every 15 minutes of every day during the 7-day duration prior to the day of interest. These data are input to the k-means clustering algorithm of SPSS using a pre-specified range of cluster outputs (ranging from 6 to 11). Ten clusters were selected by the study team to represent multiday driving based upon a minimum of 50–100 observations in each cluster and having the clusters indicate clear patterns of driving (where clarity is judged by having more than 50 percent 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 truck driver crash data (e.g., Park et al., 2005). The application of the method becomes clearer as the first driving pattern output of the cluster analysis is discussed below.

Note that the outcome during the trip of interest (i.e., a crash or non-crash) does not affect the allocation of drivers to clusters. The only variables that influence the allocation of drivers to clusters are the individual pattern of driving for each driver over the 7 days prior to the day of interest. As a result, one can quickly compare the proportion of crash-involved drivers in each cluster (i.e., the number of crash-involved drivers divided by the total number of drivers in the cluster). This provides an initial indication of the crash risk posed by different multiday driving schedules. A more refined estimate of the association of multiday driving to crash occurrence is provided by the logistic regression models described in Section 3.3, but the crash driver proportion provides an initial estimate and is used in setting up the logistic model (i.e., deciding on which pattern to use as a baseline). In the formulation of the driving patterns, driving and on duty/not driving is coded as “1”; off duty and sleeper berth is coded as “0.”

An example of one driving cluster obtained from this method is shown in Figure 4. The figure shows 8 days of driving, starting from time “0” on the horizontal scale representing midnight on the first day of driving until time 192 which is midnight on the 8th day. The vertical scale indicates the proportion of drivers in a particular duty status throughout the 8 days. The thick solid blue line indicates the proportion drivers who were driving or on duty/not driving. The thin solid green line indicates the proportion of drivers in a sleeper berth. The dashed red line indicates the proportion of drivers in off-duty status.

The 8th day is shown for information only. The cluster was determined by the pattern of driving on days 1–7 (i.e., time 0–168). There are a number of observations about multiday driving that can be made from such a figure. One observation is that drivers are on duty on days 1, 4, 5, 6, and 7 (i.e., more than 60 percent of the drivers are on duty between 6 a.m. and 11 a.m. on these 5 days); they are typically off duty on days 2 and 3 (i.e., 40 percent of the drivers are on duty at 6 a.m. on day 2, but this percentage quickly drops to 20 percent by noon). On day 3, no more than 20 percent of the drivers are on duty at any time.

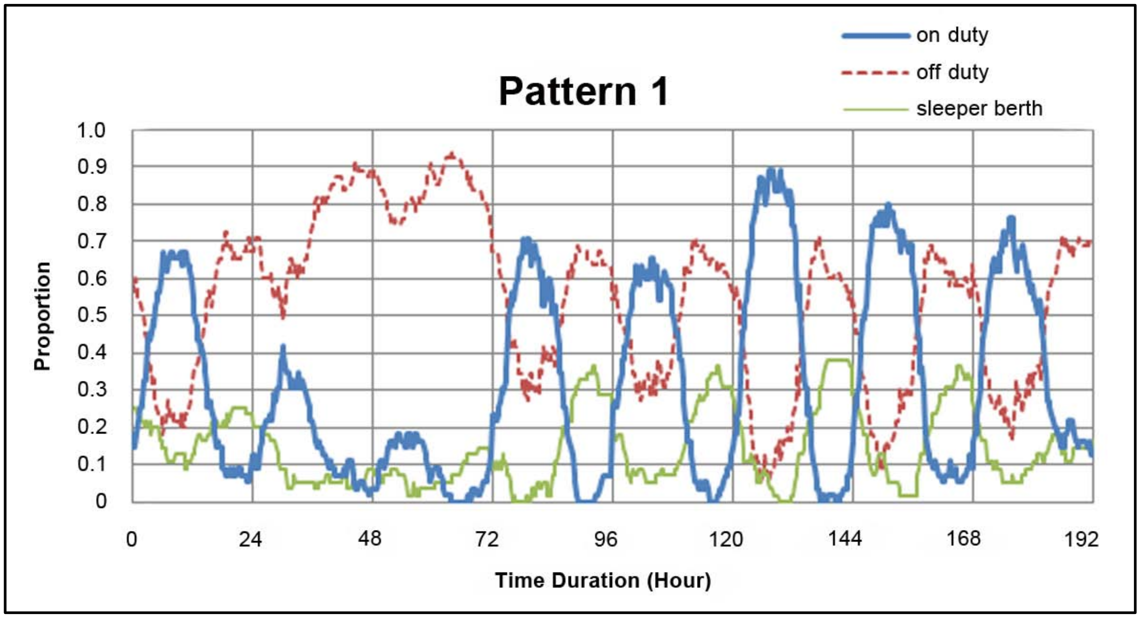

Figure 4. Output of Cluster Analysis: TL Multiday Driving Pattern 1

Considering the on-duty time, this group of drivers starts to be on-duty around midnight. Typically 20 percent of the drivers are on duty at midnight at the beginning of days 1, 4, 5, 6, and 7. The percentage of drivers on duty grows throughout the morning, reaching a peak between 6 a.m. and 11 a.m. On the first day, the percentage of drivers on duty between 6 a.m. and 11 a.m. reaches 65 percent. The maximum percentage of drivers on duty from 6 a.m. to 11 a.m. is 70 percent, 65 percent, 90 percent and 80 percent on days 4 through 7 respectively. In addition, nearly 90 percent of the drivers were on duty in the morning of the 6th day. Taken as a whole, these observations of on-duty time indicate that drivers with this pattern drive a schedule with regularity (in that more than 60 percent of the drivers with this pattern are on duty during the 6 a.m. to 11 a.m. time period during days 1, 4, 5, 6, and 7).

The drivers with this pattern of driving were typically off duty during the afternoon and night hours. By 2 p.m. on days 1, 4, 5, 6, and 7, at least 50 percent of the drivers were off duty. On these 5 days, the percentage off-duty drivers rose during the afternoon to highs of 70 percent on each of the days—typically by 4 p.m. In addition to off-duty time, some drivers (about 30 percent on days 4–7) were in a sleeper berth instead of off duty.

Therefore, this cluster represents drivers who drove a fairly regular pattern of daytime driving over days 4–7 and primarily used off-duty time when not driving, although some did use a sleeper berth. Remember, however, that the driving pattern was formed by combining driving time and on duty/not driving (as a "1") and comparing that with off-duty and sleeper berth time combined (as a "0"). The study team believes that additional insight is gained about work schedules by displaying the pattern with off-duty time and sleeper berth time separated. The study team did not attempt to construct the patterns by separating off-duty time and sleeper-berth time. The experience is that many more patterns would be developed, resulting in too few drivers being placed in each pattern.

3.5 TIME OF DAY

The time of day is coded as a series of dummy variables (see Table 6). The resolution of time of day is 2 hours and is coded as follows: midnight to 1:59 a.m. is the first period, the next is 2 a.m. to 3:59 a.m., and the final interval is 10 p.m. to 11:59 p.m. The driving time is coded as "1" and other activities are coded as "0." The rules of coding time of day are shown as follows:

- If the driver is driving for an entire time of day represented by the variable, then the driver is coded as "1" during that time of day. If the *total* driving of the last trip is less than one unit (e.g.,45 minutes or less during midnight to 1:59 a.m., then midnight to 1:59 a.m. will be coded as "1," other 11 categories are coded as "0").
- If a driver's driving time crosses more than one period (for example, driving from 1:45 a.m. to 2:30 a.m.), then the most proportional time of day will be coded (in this example from 2 a.m. to 3:59 a.m. as "1," and the duration from midnight to 1:59 a.m. as "0"). Another example is if driving covers from 1 a.m. to 2:30 a.m., then midnight to 2 a.m. is coded as "1," and 2 a.m. to 4 a.m. is coded as "0."
- If a particular driving time is evenly split between two time-of-day periods, the latter time of day is coded as driving. For example, if 60 minutes of driving is from 1:30 a.m. to 2:30 a.m., then midnight to 1:59 a.m. will be coded as "0," and 2 a.m. to 3:59 a.m. will be coded as "1."

Table 6. Coding Time of Day Variable

Driver	Driving Hour	Time of Day	T2	T_4	T6	T8	T10-T22	T_24
Crash 1	3	0_1	1	0	0	0	0	0
Crash 1	3	1_2	1	0	0	0	0	0
Crash 1	3	3_4	0	1	0	0	0	0
No Crash 1	5	23_24	0	0	0	0	0	1
No Crash 1	5	0_1	1	0	0	0	0	0
No Crash 1	5	1_2	1	0	0	0	0	0
No Crash 1	5	2_3	0	1	0	0	0	0
No Crash 1	5	4_5	0	0	1	0	0	0

3.6 DRIVING BREAK

There is an interest in better understanding the effect of breaks during driving on the probability of a crash. 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, the study team chose the term *driving break* because it represents a cessation in the driving task for a relative short period of time (typically 15 minutes to 1 hour).

The variable used to describe the driving break is derived by combining off-duty and sleeper-berth time during the trip of interest. Driving breaks are categorized into four groups: group one has drivers with no breaks; group two is those with one break; group three drivers take two breaks; and group four drivers take three or more breaks. Categorical covariates are used to quantify the influence of each group on driver's crash odds.

3.7 EXTENDED RECOVERY PERIODS

Previous research has shown a persistent correlation between extended recovery periods and the odds of a crash in the next driving period (e.g., Jovanis et al., 2005; Park et al., 2005). Particular attention in this study was paid to the occurrence of the extended time periods and the time of day when the driver returns to work after the extended time off duty. Because the data on work schedules were collected over at least 8 days and with a resolution of 15 minutes, the basic raw data supports a number of ways to explore the effect of multiday periods. Because the crash always occurs on the 8th day (i.e., the day of interest) all analyses are referenced to this day.

Specifically, one way this issue is addressed is through the use of a series of indicator variables as follows:

- The baseline is no extended recovery period (just a 10-hour off-duty period) and a daytime trip for the driver on the day of interest.
- Another indicator variable represents a trip where there is no extended recovery (again, a 10-hour off-duty period) immediately before the trip of interest but the driver returns to work at night.
- Another indicator variable represents a trip with at least 34 hours off duty (or in a sleeper) immediately before the trip of interest with a night return to duty.
- The last indicator variable is at least 34 hours off duty or in a sleeper with a return to work during the day.

These variables are tested as a group after the testing of predictors described above. This allows the study team to explore the joint effect of the recovery period and different times of return to work.

In addition to defining specific indicator variables, the multiday driving patterns can be used to assess the implications of the timing of the recovery periods with respect to the day of interest. There are no additional variables that need to be defined. However, the driving patterns need to be interpreted in a particular sequence. This analysis is demonstrated in Section 4.

3.8 INTERACTION TERMS

Interaction terms are used to gain additional insight into the link between crash odds, driving hours, and multiday driving. Interaction terms are the product of two predictor variables of interest. For example, an interaction term is driving hour 1 and pattern 1 occurring for a driver. Because there are 11 driving hours and 10 patterns, a model with all interactions at once would have an additional 110 parameters in addition to the main effects. To overcome this limitation, a series of models are estimated, one interaction at a time. For example, driving hour 1 would have a main effect and an additional 10 parameters for interactions with each of the driving patterns. The significant interactions are noted for further testing and then driving hour 2 is selected and a set of 10 interaction terms are added to the model—one for the interaction of driving hour 2 and each of the 10 patterns. Significant interactions are noted for further testing. This process continues for all 11 driving hours (see Figure 2).

After all the interactions are conducted, the significant ones are entered into the final model with only main effects. Insignificant interactions are dropped at this point. What remains are the main effects of all the variables, as well as the significant interaction terms for driving time and driving pattern.

3.9 34-HOUR RESTART ANALYSIS

The study team's approach in this portion of the research is to seek to answer the following question: what is the safety implication of adopting the 34-hour restart rule? To answer this question, the study team must be able to look back in the driver record for more than 1 week because the team would like to capture driving that has occurred between two periods of 34 hours or more off duty. As a result, only data from 2010 are used in this analysis. In addition, the study team would like to identify periods when the use of the 34-hour restart actually resulted in a driver driving more hours than would have been allowed with the previous 70-hours-in-8-days rule. This approach focuses not only on the 34 hours off duty, but an additional analysis of whether this off-duty period actually was used as a restart. If there was a restart of the driver's cumulative hour's clock, then there is a need to develop a way to associate the reset with a change in crash odds.

A slightly different modeling framework is used to explore the implications of the 34-hour restart policy. Instead of comparing crash-involved and non-crash-involved drivers, this analysis compares a crash-involved driver to his or herself. The crash day is considered the case and the prior non-crash days for the same driver are considered the control. This allows a more precise comparison within the crash-involved driver cohort because the driver is compared to his or herself. The weakness is that the drivers who do not have any crashes are removed from the analysis.

In this approach, each driver who has a crash is considered a case. This crash always occurs on the day of interest which allows the analysis to track up to 13 days prior to that crash day. In the data, the study team looked for a pattern of driving since the last 34 or more hours off duty (or in combination with a sleeper). Once this period is identified within the 13 days prior to the crash day, a series of variables are measured. The first variable is an indicator variable which is "1" if the driver would have violated the 70/8 rule *on the previous day* without the reset. This is a direct measure of the association between a crash and the immediate occurrence of the 34-hour restart to extend driving beyond the 70/8 rule. Then the next day back is examined to see if there would have been a violation 2 days before, not the day before. This process continues progressively through the previous days to allow the analysis to identify the occurrence of the "pseudo-violation" and when during the prior few days the pseudo-violation occurred. This process is repeated for each driver until a day is reached where the driver is no longer driving (i.e., the time of the 34-hour restart).

Next the immediate previous day is considered a control (i.e., it did not have a crash) and a check is made if it is immediately preceded by a 34-hour or more off-duty period. This would associate the occurrence of the restart with a non-crash outcome. This process is continued for each day until the driver stops driving (i.e., has an entire day devoted to not driving) which occurs at some point in the record if the driver had a 34-hour restart. Thus, a non-crash outcome is generated for the day just before the crash day, and a series of predictors are associated with the non-crash event for this particular driver. The process is repeated for each prior day as a control until the day is reached when the driver no longer drives (i.e., the restart day).

Using this method, a series of cases (crash outcomes) are generated, along with a series of controls (non-crash outcomes), and a string of additional predictor variables related to the timing and occurrence of pseudo-violations of the 70/8 rule.

An additional predictor variable is developed to explore the implications of driving schedules in which the pseudo-violation occurs for 2 consecutive days. This may be considered a measure of the intensity of the driving and the compactness of the driver's schedule over multiple days. Separate variables are defined for pseudo-violation on the 1st and 2nd day previous to the crash day; the 2nd and 3rd day prior; the 3rd and 4th, etc. In addition, the model considers whether the trip of interest began at night (defined as between 6 p.m. and 6 a.m.) and whether a recovery period (i.e., off duty and sleeper time greater than 34 hours) occurred just prior to the trip of interest. A list of the variables used in the model is summarized in Table 7.

Table 7. Summary of Variables Used in 34-Hour Restart Analysis

Variable Name	Type	Definition
Pseudo 1	Indicator	Coded as a 1 if driver had pseudo-violation on day prior to trip
Pseudo 2	Indicator	Coded as a 1 if driver had pseudo-violation 2 days prior to trip
Pseudo 3	Indicator	Coded as a 1 if driver had pseudo-violation 3 days prior to trip
Pseudo 12	Indicator	Coded as a 1 if driver had pseudo-violation on day prior and 2nd day prior
Pseudo 23	Indicator	Coded as a 1 if driver had pseudo-violation 2 days prior and 3 days prior
Night	Indicator	Coded as a 1 if driver drove between 6 p.m. and 6 a.m.
Recovery 34	Indicator	Coded as a 1 if driver had a recovery period on the day immediately prior

3.10 AGGREGATE ANALYSIS

In order to support the rulemaking activity, a request was made to develop one logistic regression model with all the data. This model is described in Section 4 and includes most of the predictors used in the carrier-based analysis, except for driving pattern and recovery formulation. Driving patterns were not used because they were developed from separate data for TL and LTL carriers and cannot be combined into a single model. The study team adopted a simpler approach to recovery modeling by using an indicator variable which is “1” if there was a recovery immediately before a trip of interest and “0” otherwise.

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4. DATA ANALYSIS

4.1 DATA ANALYSIS FOR TRUCKLOAD CARRIERS

4.1.1 Driving patterns

Before inclusion in logistic regression models, a series of analyses were conducted with the TL data to identify and summarize common multiday driving programs. As described in Section 3, the driving pattern of every driver (each 15 minutes of every hour for all 24 hours of each of 7 days prior to the day of interest) was described as the driver being on duty/not driving or driving (coded as “1”) compared to in a sleeper berth or off duty (coded as “0”). This yields a string of 672 dichotomous variables which describe the specific pattern for each driver. Initially, 959 drivers were identified as TL drivers, but missing data reduced the number of available drivers to 878. These drivers’ multiday driving schedules were entered into a k-means cluster analysis. The study team manually examined clusters numbering from 6 to 11, deciding that 10 clusters provided the most distinct interpretable results. It is important to remember that the allocation of drivers to clusters is independent of whether or not the driver had a crash, because only the 7 days prior to the crash day are used in the cluster analysis.

Table 8 summarizes the outcome of the analysis using 10 clusters or driving patterns. The table indicates the number of crash and non-crash drivers in each cluster along with an estimate of the relative crash risk. Because cluster 5 had the highest proportion of crash-involved drivers (46 of 96 or nearly 50 percent), it is considered the baseline (i.e., a Relative Risk (RR) = 1.00). All other clusters are measured *relative* to that cluster.

Table 8. Crash Relative Risk for TL Multiday Driving Patterns

Driving Pattern	Number Crashes	Number Non-Crashes	Total	RR
1	13	42	55	0.49
2	27	62	89	0.63
3	39	51	90	0.90
4	27	46	73	0.77
5	46	50	96	1.00
6	21	60	81	0.54
7	42	103	145	0.60
8	27	36	63	0.89
9	40	67	107	0.78
10	36	43	79	0.95
Total	318	560	878	N A

Clusters 1, 2, 6 and 7 have relative crash risks below 0.70; Clusters 3–5 and 8–10 have relative risks above 0.70. The highest relative risks are for clusters 3, 5, 8, and 10, with values of 0.90, 1.00, 0.89, and 0.95, respectively. The results in Table 8 provide the first evidence that multiday driving patterns may result in different levels of crash probability. Using the clusters as predictors in the logistic regression will provide a more definitive estimate of crash odds associated with the driving patterns captured by each cluster. As such they will be hereafter referred to as driving patterns.

Additional information about each pattern is contained in Table 9 and Table 10 which summarize the average on-duty and off-duty time for each day for each pattern, respectively. Recall from the discussion in Section 3.4 that pattern 1, the one with the lowest relative risk, had drivers scheduled from early morning to early evening regularly during days 4–7. Drivers tended to be off duty during days 2 and 3. This is confirmed in Table 10 as the off-duty time increases to 17–20 hours during days 2 and 3.

Figure 4 through 12 and 14 summarize the multiday driving represented by each of the cluster analysis outputs. After each figure, there is a summary interpretation of the driving pattern and its potential connection to odds of a crash.

In pattern 2 (Figure 5), one sees that the drivers are on duty in the middle of the day (more than 50 percent of the drivers are on duty between 8 a.m. and about 8 p.m. with a peak of almost 80 percent on duty at noon on days 3–6). The peak is 70 percent on duty on day 7 at noon as well. Only 40 percent of the drivers are on duty at noon on days 1 and 2, indicating that many use this as a recovery period. Most of the drivers in this pattern use a sleeper berth when not driving during days 3–7; 60 percent of drivers use a sleeper berth in the early morning of day 3. This use of a sleeper increases to between 70 and 75 percent during the late night and early morning hours of days 4–7. Notice that days 1 and 2 show a mix of on-duty time and sleeper-berth/off-duty time. When not on duty, almost 50 percent of the drivers are off duty at 10 p.m. on day 1 (and about the same percentage on day 2), while slightly more than 40 percent are in a sleeper berth (about 35 percent at the end of day 2). While some drivers appear to be taking their recovery period during these days, others are not. This pattern is among the group with the lower crash relative risk (i.e., 0.63).

Table 9. Summary of On-Duty Time for 10 Driving Patterns for TL Drivers

Driving Pattern	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Sum of Averages
1	8.536	4.259	2.041	7.9	7.941	10.345	9.627	50.65
2	4.812	5.36	9.124	8.618	8.871	8.494	7.601	52.88
3	9.444	10.125	6.367	1.286	4.678	9.217	9.9	51.02
4	7.524	1.373	1.031	8.462	9.921	9.579	9.99	47.88
5	7.411	5.063	2.667	1.435	4.5	7.076	7.81	35.96
6	7.034	6.17	7.111	7.713	7.728	6.398	8.321	50.48
7	8.659	8.505	8.829	8.371	7.762	7.978	7.719	57.82
8	9.5	9.849	10.107	7.381	5.429	3.972	7.036	53.27
9	9.834	9.661	9.273	8.986	6.668	2.57	4.801	51.79
10	7.557	7.826	7.87	7.494	7.234	6.699	7.94	52.62

Table 10. Summary of Off-Duty Time for 10 Driving Patterns for TL Drivers

Driving Pattern	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Sum of Averages
1	10.955	17.664	20.15	12.373	11.923	9.327	10.118	92.51
2	13.39	12.772	7.121	7.132	7.343	7.416	8.124	63.30
3	10.078	9.55	14.183	19.942	16.939	11.622	10.094	92.41
4	12.555	21.13	21.243	11.877	7.908	7.545	6.784	89.04
5	10.073	14.229	18.286	20.826	16.625	11.385	8.844	100.27
6	11.966	13.793	11.92	10.944	11.336	12.577	10.574	83.11
7	7.195	6.605	5.752	6.221	7.314	7.138	7.281	47.51
8	10.107	9.897	9.865	12.762	15.373	17.266	12.944	88.21
9	8.217	7.797	8.136	8.65	12.671	17.785	14.871	78.13
10	9.627	9.25	8.832	8.358	9.566	10.212	9.035	64.88

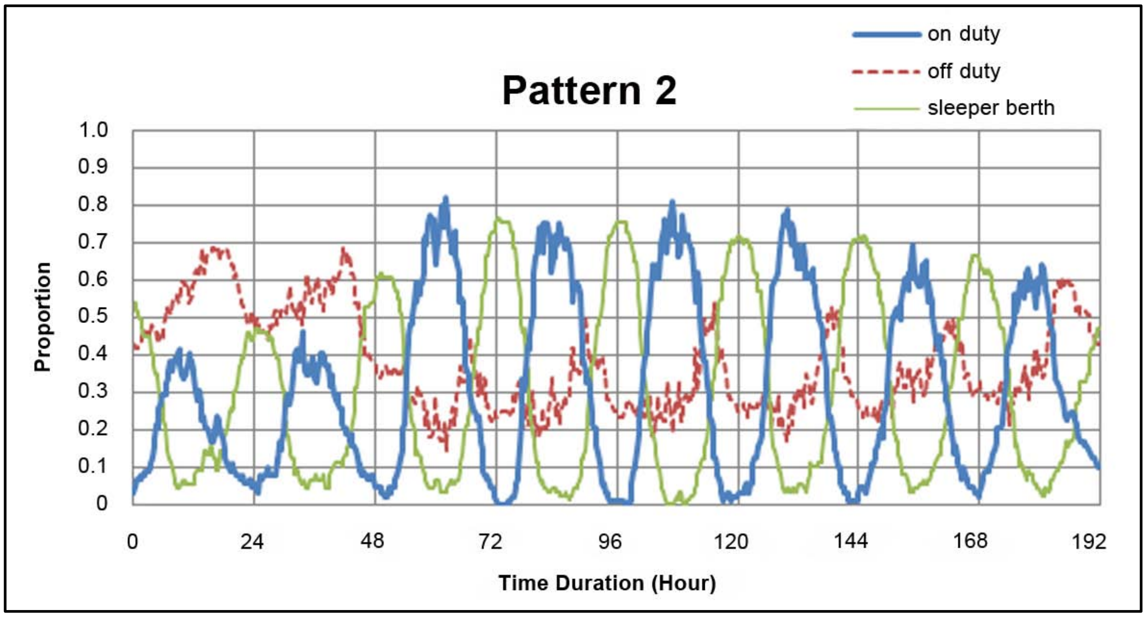


Figure 5. Summary of Multiday TL Driving Pattern 2

The work schedules of drivers in pattern 3 are illustrated in Figure 6. Drivers are on duty in the morning and early afternoon, with more than 50 percent on duty between 8 a.m. and 8 p.m. on days 1, 2, 6, and 7, with a peak on those days of more than 80 percent at noon. A smaller proportion of the drivers are on duty on days 3 and 5 with a maximum of 60 percent at noon on day 3 and 45 percent on day 5. Day 4 is dominated by off-duty and sleeper-berth time as more than 60 percent of the drivers are off duty at noon on day 4. The study team's interpretation of this pattern is that some drivers take their recovery on days 3 and 4 while others take it on days 4 and 5. This pattern has much in common with pattern 2—there is daytime driving and nighttime off-duty time. The primary difference is that pattern-3 drivers have their recovery during days 3 and 4 while pattern-2 drivers' recovery periods are during days 1 and 2. This driving pattern is in the group with elevated crash relative risk of 0.90.

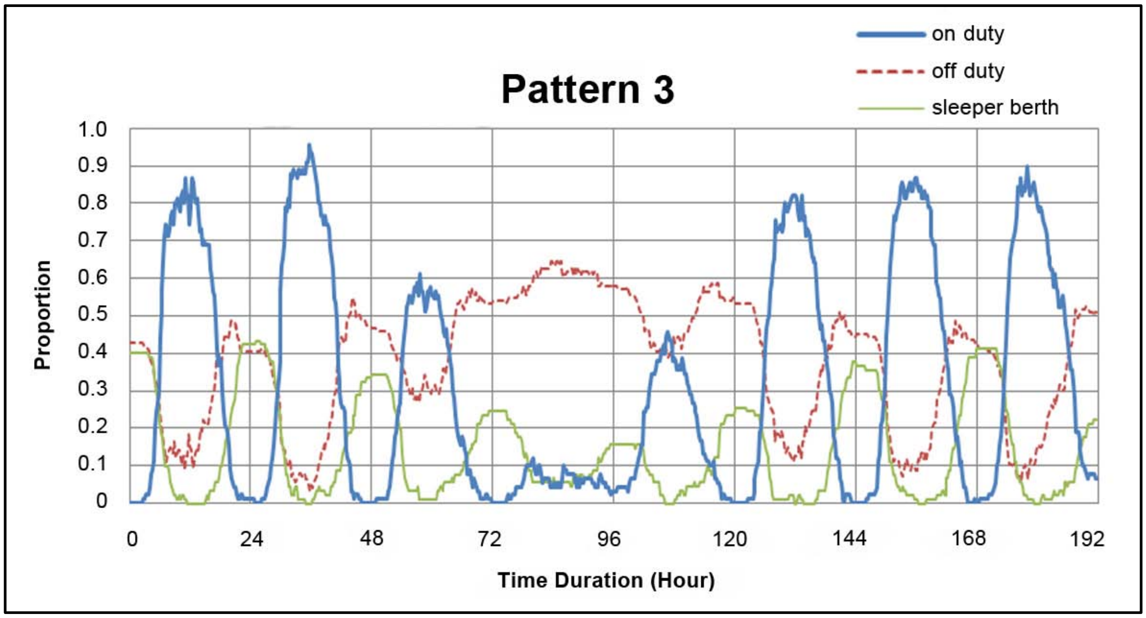


Figure 6. Summary of Multiday TL Driving Pattern 3

Pattern 4 is illustrated in Figure 7, again showing regular midday daytime driving, but this time during days 1, 4, 5, 6, and 7. The recovery period for this group is more firmly defined as more than 80 percent of the drivers are off duty continuously during days 2 and 3. Sleeper berths are little used on days 2 and 3 but are used almost 60 percent of the time in the late night and early morning periods of days 4–7. Pattern 4 is similar to patterns 2 and 3 except the recovery period is very sharply defined and occurs on days 2 and 3. The relative risk for drivers in this group is 0.77—between the values for patterns 2 and 3.

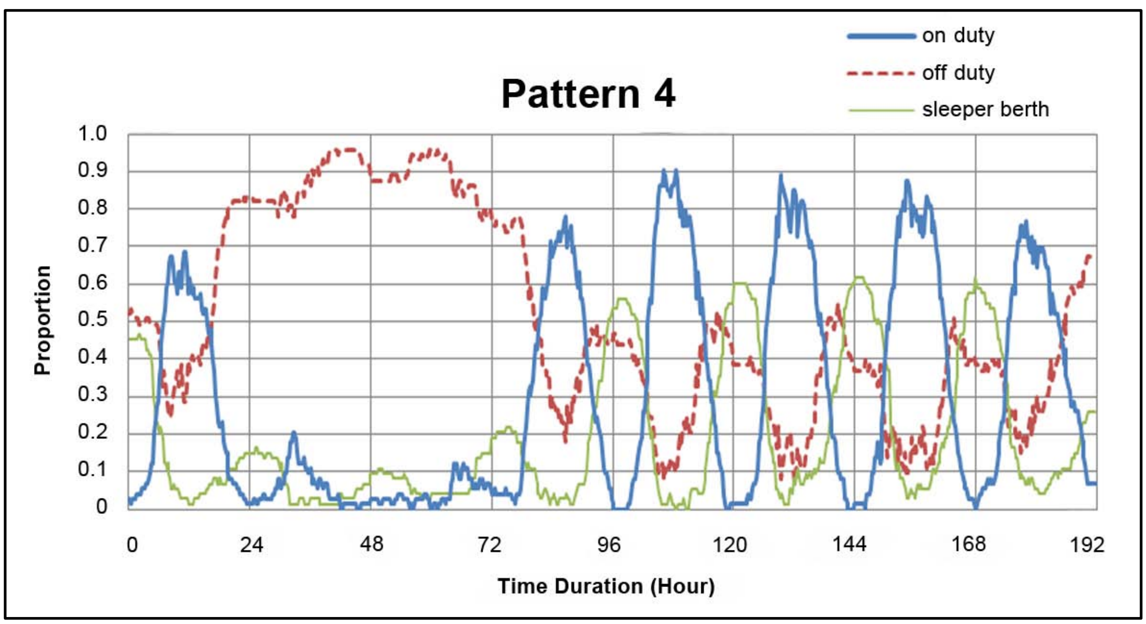


Figure 7. Summary of Multiday TL Driving Pattern 4

Driving pattern 5 with the highest relative crash odds is shown in Figure 8. Obviously, this pattern has the highest proportion of off-duty time throughout the 8 days, but particularly in days 3–5. This observation is supported by the average on-duty time in Table 9 for this group of drivers. The percentage of drivers off duty starts at 50 percent at the end of day 1 and increases to 70 percent at the end of day 2, 82 percent at the end of day 3 and more than 90 percent at noon on day 4. On days 6 and 7, sleeper berth usage peaks at more than 60 percent at 2 a.m. on both days. This multiday pattern has the highest relative crash risk (baseline or 1.0). One possible factor could be that drivers are coming off extended time off duty, returning to work and driving from early afternoon to late at night. Thus, there is a possible combination of late night driving occurring with long driving times. One might also speculate that cumulative fatigue or sleep debt may be playing a role as this pattern with the highest crash odds occurs after 2 full days of driving.

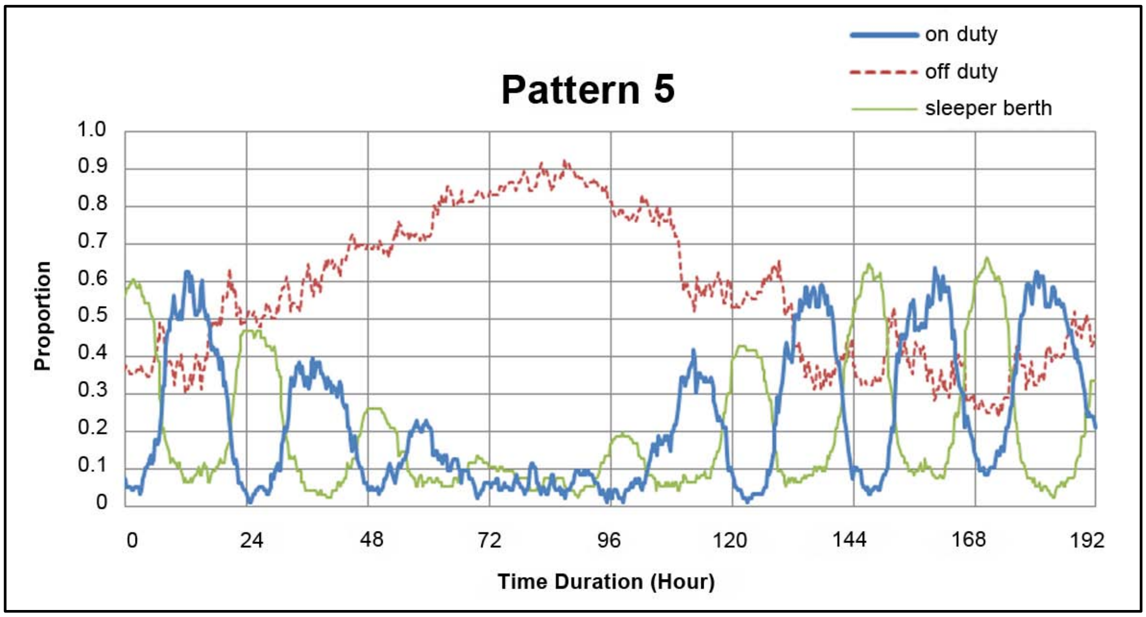


Figure 8. Summary of Multiday TL Driving Pattern 5

Driving pattern 6, summarized in Figure 9 is a schedule with relative crash risk of 0.54. On-duty time occurs during late night and early morning hours. More than 60 percent of the drivers are on duty on days 3–7. Even on days 1 and 2, slightly more than 50 percent of the drivers are on duty by midnight. Off-duty time is centered around noon on all 7 days; more than 60 percent are off duty on days 3–7, but more than 70 percent are off duty on day 2. This pattern appears to be a composite of drivers with common on-duty and off-duty times each day, but with different days within the 7-day period when the on-duty time occurs. Notice that the peak is 60 percent on duty for days 3–7, so 30 to 40 percent are off duty or in a sleeper berth. This appears to be a driving pattern with two underlying schedules in use.

Pattern 7, illustrated in Figure 10, has a low relative crash risk of 0.60. This is another pattern that shows on-duty time centered on noon every day. Between 60 and 80 percent of drivers are on duty on any of days 1–7 at this time. The sleeper berth is regularly used when not on duty as 70 to 85 percent of drivers use the sleeper berth centered around midnight on all days. This is a sharp and regular pattern, but one should not infer that all drivers are driving all days. It seems more likely that pattern 7 is an aggregation of drivers with this pattern over 7 days but who have different days off during that period.

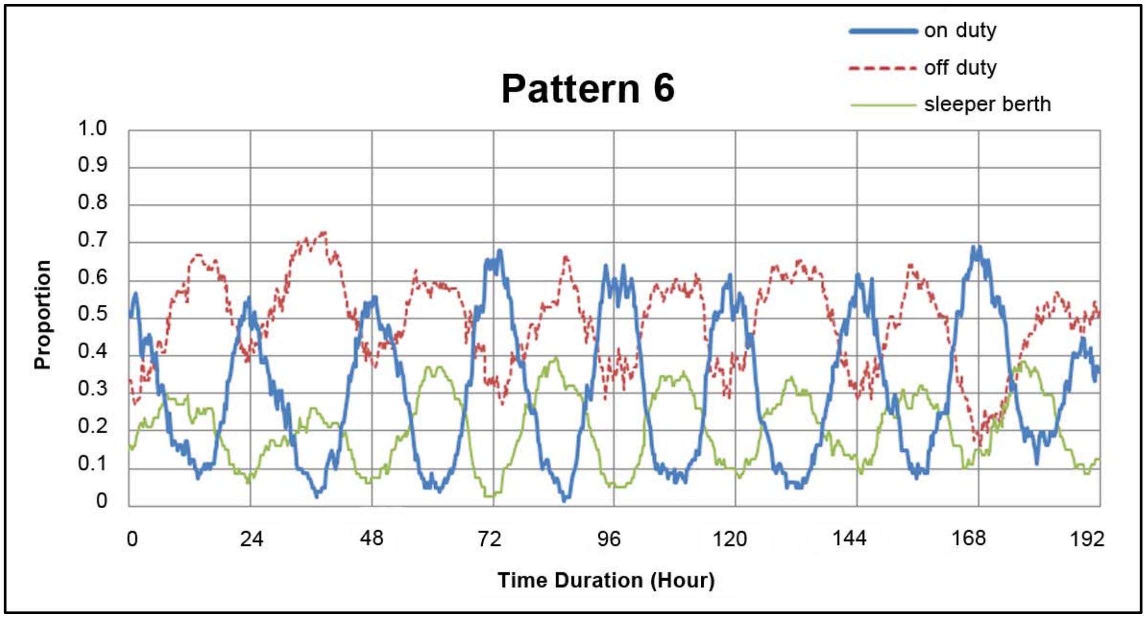


Figure 9. Summary of Multiday TL Driving Pattern 6

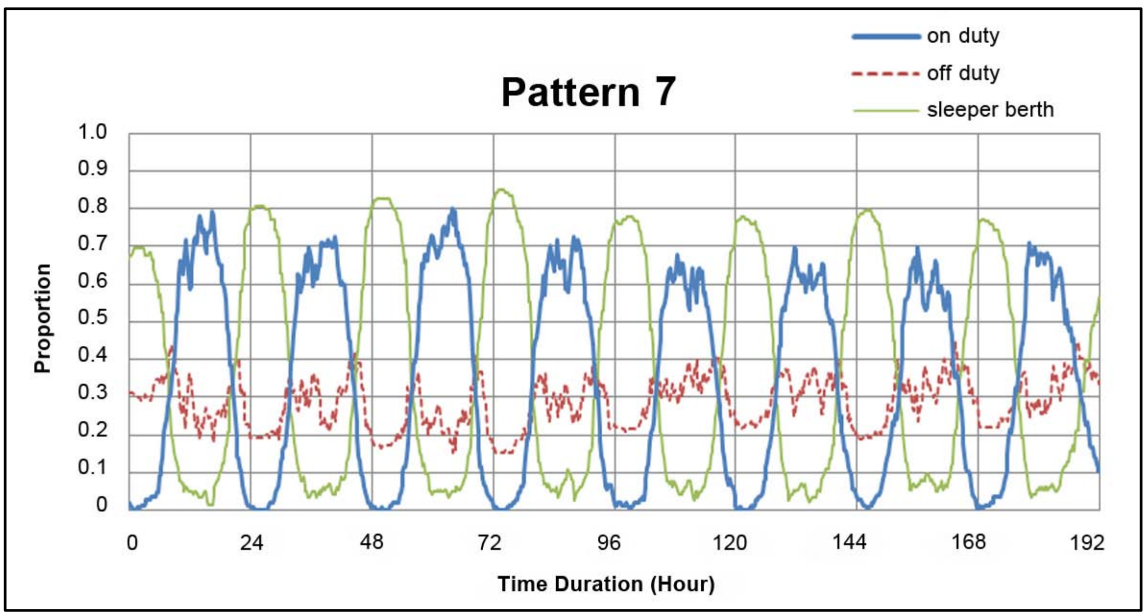


Figure 10. Summary of Multiday TL Driving Pattern 7

Driving pattern 8, summarized in Figure 11, has a high relative crash risk of 0.89. Drivers are on-duty from early morning into early afternoon. On days 1–4 and day 7, at least 50 percent of the drivers are on duty by 2 a.m. The percentage of drivers on duty peaks at 80 to 90 percent on these 5 days. Off-duty time occurs from afternoon into evening, and recovery occurs in the afternoon of day 5 and into day 6. Drivers use off-duty time for their breaks, and a maximum of 30 percent of the drivers use sleeper berths during the days of frequent driving.

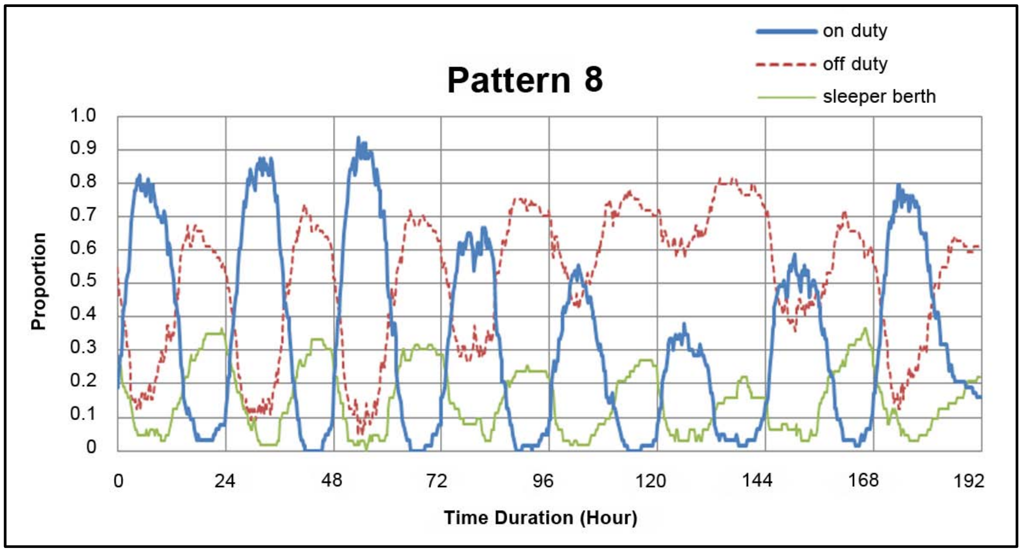


Figure 11. Summary of Multiday TL Driving Pattern 8

Driving pattern 9, summarized in Figure 12, has a relative crash risk of 0.78. Drivers are on duty during midday, particularly for days 1–4. Both off-duty time and sleeper berths are used when not on duty. The recovery period occurs during days 6 and 7. This pattern is similar to patterns 2, 3, and 4, in that on-duty time occurs at relatively the same time each day (other than recovery). It seems likely that these four patterns are actually the same driving pattern that is captured at four different points in time with respect to the recovery period.

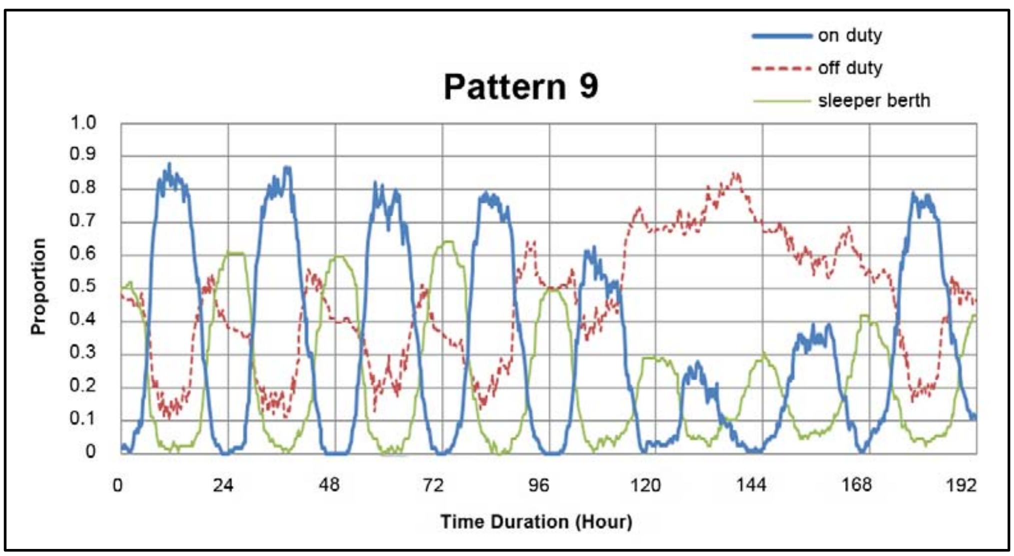


Figure 12. Summary of Multiday TL Driving Pattern 9

The trend in shifting recovery period with the same relative stable on-duty and off-duty times of day can be better seen in Figure 13, along with each pattern’s relative risk from Table 8.

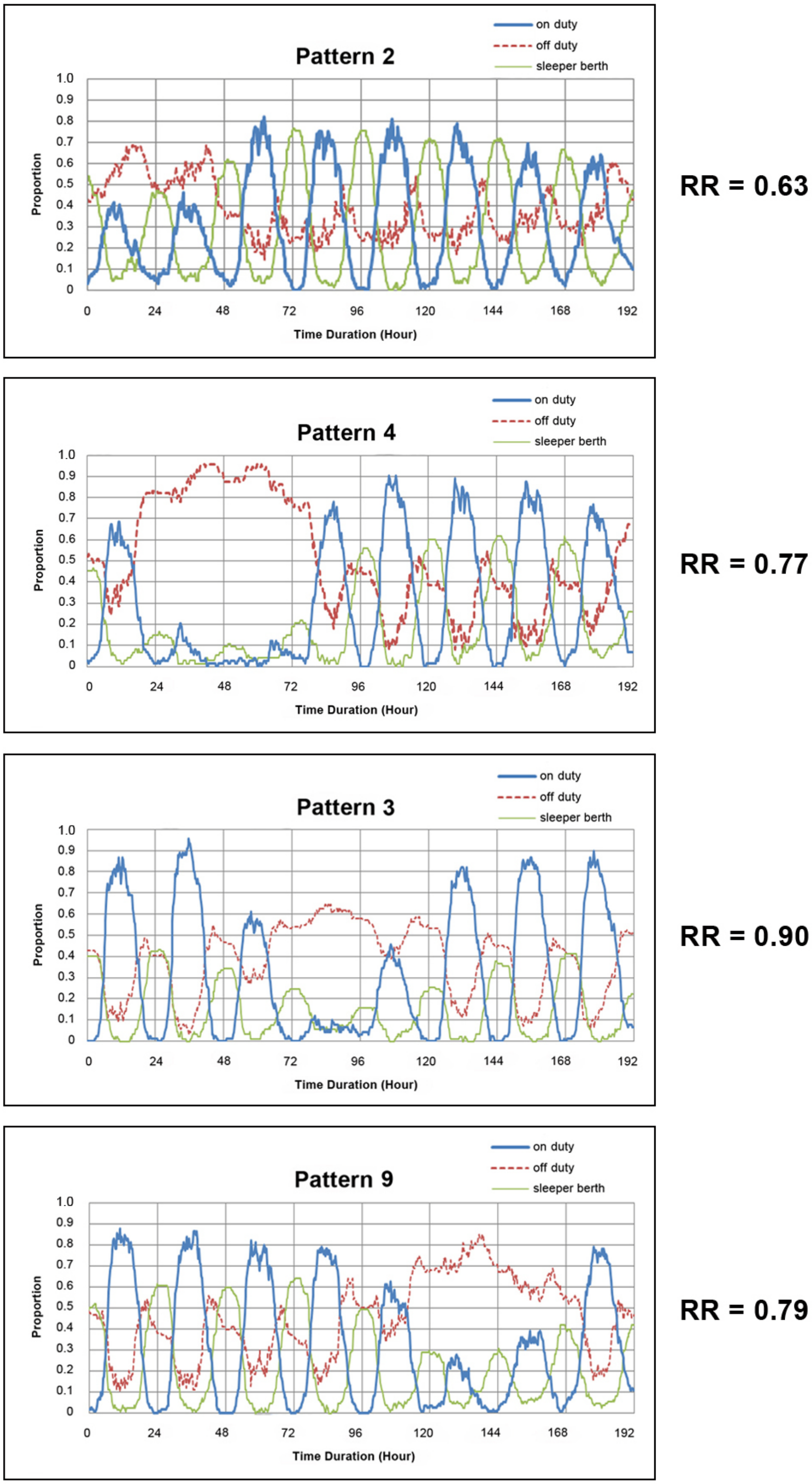


Figure 13. Trend in Shifting Recovery Period for Patterns 2, 3, 4, and 9

One can track the relative movement of the recovery period over the 7 day period: from days 1 and 2 in pattern 2, to days 2 and 3 in pattern 4, to days 4 and 5 in pattern 3, and then days 6 and 7 in pattern 9. Also notice that the closer the recovery is to day 7, the higher the relative risk. This is, the team believes, evidence that the immediate trip after a recovery period carries relatively higher relative risk. These findings are tentative, however, and await further testing with quantitative statistical models.

Pattern 10 drivers (Figure 14) have a high relative risk (0.95) and, as a group, are somewhat difficult to classify. The driving pattern over the 7 days is somewhat regular, but typically not more than 60 percent of drivers are on duty at the same time. Both sleeper berth and off-duty status are used for relief from work and driving. Drivers typically spread their hours to be on duty over all 8 days, with on-duty time falling in late night and early morning.

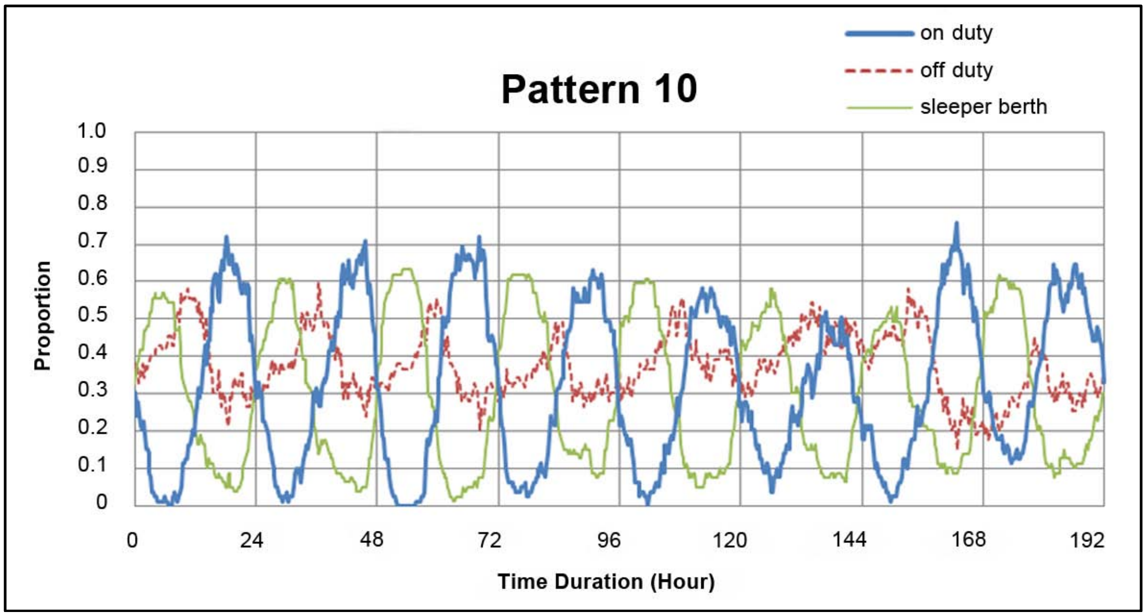


Figure 14. Summary of Multiday Driving Pattern 10

4.1.2 The time-dependent logistic regression models

As described in Section 3, the basic modeling structure used in this study is time-dependent logistic regression. This section presents a sequence of models that represent the implementation of the modeling framework shown in Figure 2. The definition of each predictor variable used in this section is summarized in Table 11. Each of the variables is sequentially added to the logistic regression model to test if the variable improves model fit as a whole. At the same time, as predictor variables were added, changes in model parameters were tracked. The statistical estimation of the driving time model is shown in Table 12.

Table 11. Variable Glossary of Time-Dependent Logistic Regression Models

Variable Name	Definition
Crash	Dependent variable. Crash=1 if the driver has a crash during the last trip, otherwise=0.
Covariates of Driving Hour of the Last Trip	
dh1	dh1=1 if driving hour of the last trip is of duration 0–1 hours, otherwise=0.
dh2	dh2=1 if driving hour of the last trip is of duration 1.25–2 hours, otherwise=0.
dh3	dh3=1 if driving hour of the last trip is of duration 2.25–3 hours, otherwise=0.
dh4	dh4=1 if driving hour of the last trip is of duration 3.25–4 hours, otherwise=0.
dh5	dh5=1 if driving hour of the last trip is of duration 4.25–5 hours, otherwise=0.
dh6	dh6=1 if driving hour of the last trip is of duration 5.25–6 hours, otherwise=0.
dh7	dh7=1 if driving hour of the last trip is of duration 6.25–7 hours, otherwise=0.
dh8	dh8=1 if driving hour of the last trip is of duration 7.25–8 hours, otherwise=0.
dh9	dh9=1 if driving hour of the last trip is of duration 8.25–9 hours, otherwise=0.
dh10	dh10=1 if driving hour of the last trip is of duration 9.25–10 hours, otherwise=0.
dh11	dh11=1 if driving hour of the last trip is of duration 10.25–11 hours, otherwise=0.
Covariates of Driving Patterns	
Pattern 1	c1=1 if the trip is driving pattern 1, otherwise =0.
Pattern 2	c2=1 if the trip is driving pattern 2, otherwise= 0.
Pattern 3	c3=1 if the trip is driving pattern 3, otherwise=0.
Pattern 4	c4=1 if the trip is driving pattern 4, otherwise=0.
Pattern 5	c5=1 if the trip is driving pattern 5, otherwise=0.
Pattern 6	c6=1 if the trip is driving pattern 6, otherwise=0.
Pattern 7	c7=1 if the trip is driving pattern 7, otherwise=0.
Pattern 8	c8=1 if the trip is driving pattern 8, otherwise=0.
Pattern 9	c9=1 if the trip is driving pattern 9, otherwise=0.
Pattern 10	c10=1 if the trip is driving pattern 10, otherwise=0.
Covariates of Time of Day	
T_2	T_2=1 if midnight to 2 a.m. is driving time, otherwise=0.
T_4	T_4=1 if 2 a.m. to 4 a.m. is driving time, otherwise=0.
T_6	T_6=1 if 4 a.m. to 6 a.m. is driving time, otherwise=0.
T_8	T_8=1 if 6 a.m. to 8 a.m. is driving time, otherwise=0.
T_10	T_10=1 if 8 a.m. to 10 a.m. is driving time, otherwise=0.
T_12	T_12=1 if 10 a.m. to noon is driving time, otherwise=0.
T_14	T_14=1 if noon to 2 p.m. is driving time, otherwise=0.
T_16	T_16=1 if 2 p.m. to 4 p.m. is driving time, otherwise=0.
T_18	T_18=1 if 4 p.m. to 6 p.m. is driving time, otherwise=0.
T_20	T_20=1 if 6 p.m. to 8 p.m. is driving time, otherwise=0.
T_22	T_22=1 if 8 p.m. to 10 p.m. is driving time, otherwise=0.
T_24	T_24=1 if 10 p.m. to midnight is driving time, otherwise=0.
Covariates of Driving Breaks During the Last Trip	
B12_0	B_0=1, if the last trip does not include any breaks (baseline), otherwise=0.
B12_1	B_1=1, if the last trip does include one break, otherwise=0.
B12_2	B_2=1, if the last trip does include two breaks, otherwise=0.
B12_3	B_3=1, if the last trip does include three and more breaks, otherwise=0.
Covariates of 34-Hour Recovery	
No 34H_Day	No 34H_Day=1, if there is no 34-hour recovery and return to work–day, otherwise=0.
No 34H_Night	No 34H_Night=1, if there is no 34-hour recovery and return to work–night, otherwise=0.
34H_Day	34H_Day=1, if there is a 34-hour recovery and return to work–day, otherwise=0.
34H_Night	34H_Night=1, if there is a 34-hour recovery and return to work–night, otherwise=0.
Recovery	A 1 if driver had recovery period immediately before day of interest, otherwise=0

4.1.3 Driving time as a predictor

Table 12 summarizes the results of the logistic regression model for driving time for TL carriers. The first five columns show the typical fit statistics for each parameter in the model. Driving time has an inconsistent effect on crash odds for these drivers. Driving hours 2, 5, and 9 show reductions in crash odds and hour 11 shows an increase compared to hour 1. Columns 6, 7, and 8 show the odds ratio (OR) for the hour (compared to the first hour which is the baseline) and the lower and upper 95-percent confidence interval (CI) respectively. The last hour shows a 226-percent increase in crash odds. Figure 15 shows the odds ratios plotted for easier comprehension. The improvement of overall fit is judged by using the Akaike Information Criterion (AIC)—a measure of the relative goodness of fit of a statistical model while adjusting for the number of parameters in the model—which has a value of 2,407.9. This value will be used to test the significance of adding additional predictors to the model.

This model shows no consistent trend relating crash odds to hours driving. The study team believes that the crash-odds increase in the last hour is in need of further analysis. At least a portion of the increase in odds may be attributable to the low sample size of observations in the last hour of driving (9 crashes of 318 TL crashes in the data; see Table 3). Additional models are estimated with LTL carriers and with the data as a whole to further explore the trend in the data.

Table 12. Crash Odds as Function of Driving Time—TL Carriers

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-2.595	0.133	-19.549	0.000	n/a	n/a	n/a
dh2	-0.385	0.211	-1.826	0.068	0.680	0.450	1.029
dh3	-0.194	0.206	-0.942	0.346	0.824	0.551	1.233
dh4	-0.105	0.207	-0.508	0.612	0.900	0.599	1.352
dh5	-0.328	0.230	-1.430	0.153	0.720	0.459	1.129
dh6	-0.279	0.238	-1.171	0.241	0.757	0.474	1.207
dh7	0.011	0.234	0.049	0.961	1.011	0.640	1.600
dh8	0.081	0.254	0.320	0.749	1.085	0.659	1.785
dh9	-0.550	0.365	-1.506	0.132	0.577	0.282	1.180
dh10	-0.296	0.440	-0.672	0.502	0.744	0.314	1.762
dh11	1.181	0.395	2.993	0.003	3.258	1.503	7.061

AIC = 2,407.9.

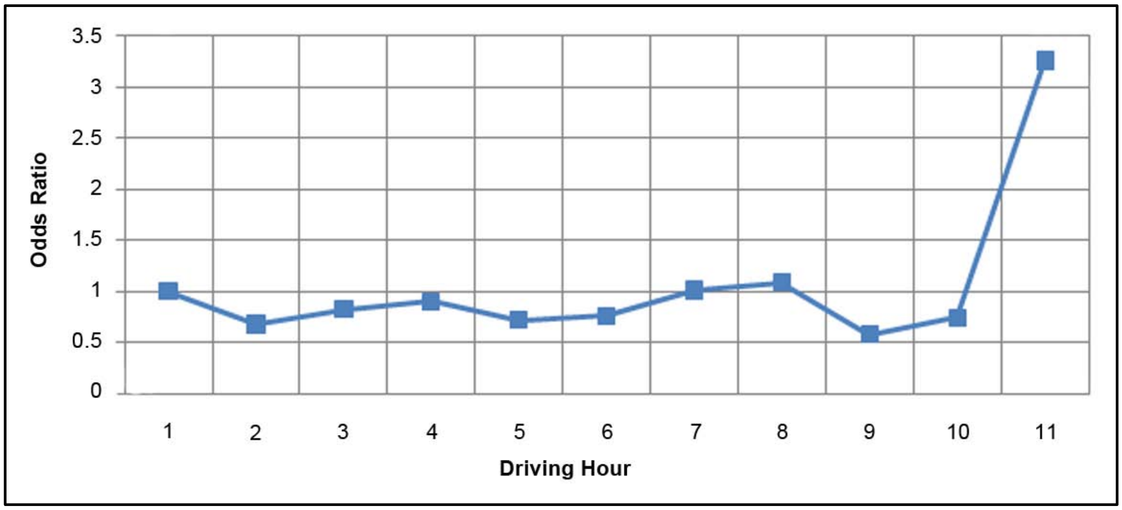


Figure 15. Trend in Crash Odds with Driving Time—TL Drivers

4.1.4 Adding multiday driving patterns as predictors

Pattern 5 has the highest relative crash risk (see Table 8), so it is designated as a baseline (i.e., reference) category for quantitative modeling. All odds ratios are referenced to pattern 5. Of immediate note is that the parameters of driving time for all driving times through 11 hours changed very little when multiday clusters were added (compare coefficients for variables dh2 through dh11 in Table 12 and Table 13). This is an indication that the multiday pattern variable is generally statistically independent of the multiday driving variable.

Considering the multiday patterns themselves, the coefficient estimates follow the trends in relative risk in Table 8. Patterns 1, 2, 6, 7, and 9 show differences from the baseline, using the significance probability, $p = 0.20$ as discussed in Section 3.2. The crash odds for drivers in pattern 1 are 58 percentage points lower than for the baseline pattern 5. The drivers who have pattern 2, 6, 7, and 9 decreased crash odds of the following percentage points: 30, 53, 48, and 30 respectively. The interpretation of the crash odds are substantively the same as contained in the discussion of Table 8, so they are not repeated here. The logistic regression provides further quantification of the importance of multiday driving in assessing crash odds for TL carriers. The overall goodness-of-fit of the model improved to an AIC of 2,406. The rule of thumb for AIC decrease is about 6 points to be considered important or “significant.” This decrease does not meet that rule of thumb.

Additional drop in AIC is possible by reducing the number of parameters estimated (e.g., combining categories that have non-significant coefficients such as pattern 3 and 8 into the baseline). It may also be possible to combine some of the significant variables with similar coefficient estimates and standard errors (e.g., pattern 2, pattern 4, and possibly pattern 9). This may improve the model-fit statistic but not help much in interpreting the model. Of greater interest is the possibility of an interaction between the multiday patterns and driving time. To model these potential effects correctly, there is a need to include all the driving times and all the driving patterns as main effects and then test for the significance of interactions. These analyses are discussed in the next section.

Table 13. Crash Odds as Function of Driving Time and Multiday Driving Pattern—TL Drivers

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-2.251	0.195	-11.557	0.000	n/a	n/a	n/a
dh2	-0.383	0.211	-1.810	0.070	0.682	0.451	1.032
dh3	-0.186	0.206	-0.905	0.366	0.830	0.554	1.243
dh4	-0.093	0.208	-0.449	0.653	0.911	0.606	1.369
dh5	-0.312	0.230	-1.357	0.175	0.732	0.466	1.149
dh6	-0.266	0.239	-1.116	0.264	0.766	0.480	1.223
dh7	0.012	0.234	0.053	0.958	1.013	0.639	1.603
dh8	0.083	0.255	0.327	0.743	1.087	0.660	1.791
dh9	-0.539	0.366	-1.473	0.141	0.583	0.285	1.195
dh10	-0.276	0.441	-0.626	0.531	0.759	0.320	1.800
dh11	1.209	0.398	3.039	0.002	3.350	1.536	7.307
Pattern 1	-0.863	0.323	-2.675	0.007	0.422	0.224	0.794
Pattern 2	-0.353	0.252	-1.402	0.161	0.703	0.429	1.151
Pattern 3	-0.133	0.227	-0.585	0.559	0.875	0.561	1.367
Pattern 4	-0.297	0.252	-1.181	0.238	0.743	0.453	1.217
Pattern 6	-0.753	0.272	-2.772	0.006	0.471	0.277	0.802
Pattern 7	-0.647	0.221	-2.928	0.003	0.524	0.339	0.807
Pattern 8	-0.183	0.253	-0.725	0.469	0.833	0.508	1.366
Pattern 9	-0.362	0.225	-1.609	0.108	0.696	0.448	1.082
Pattern 10	-0.126	0.233	-0.541	0.588	0.882	0.559	1.391

AIC = 2,406.0

4.1.5 Adding interaction terms for driving time and multiday schedules

A series of models were estimated to identify and screen significant interaction terms. The interaction of each driving hour with each driving pattern was estimated in a separate model (e.g., driving hour 1 and the 10 multiday patterns in the first model). Significant interactions in this model were retained for additional model testing. A series of 10 models were estimated (see discussion of Figure 2). The significant interactions from each of these 10 models were then entered in an additional model with driving time and pattern main effects. The predictors shown in Table 14 are those remaining after the last insignificant interactions were removed. This procedure was used in previous research (Lin et al., 1993) and allows the testing of a large number of potential interactions in a pair-wise approach.

The addition of interaction terms reduced the AIC to 2,384.3 from 2,407.9. Parameter estimates for driving hours 1–5 remained substantially unchanged, but hours 6–11 have changed in magnitude. This is a reflection of their inclusion in at least one significant interaction term (see Table 14). Driving pattern main effects also changed for patterns 3 and 4 and a small amount for pattern 7.

Table 14. Crash Odds as Function of Driving Time, Multiday Driving Pattern, and Interactions—TL Drivers

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI got OR
(Intercept)	-2.277	0.205	-11.089	0.000	n/a	n/a	n/a
dh2	-0.382	0.212	-1.806	0.071	0.682	0.451	1.033
dh3	-0.187	0.206	-0.905	0.365	0.830	0.554	1.243
dh4	-0.093	0.208	-0.448	0.654	0.911	0.606	1.370
dh5	-0.311	0.230	-1.353	0.176	0.732	0.466	1.150
dh6	-0.671	0.289	-2.322	0.020	0.511	0.290	0.901
dh7	-0.454	0.307	-1.481	0.139	0.635	0.348	1.158
dh8	-0.143	0.285	-0.503	0.615	0.866	0.496	1.514
dh9	-0.845	0.437	-1.935	0.053	0.430	0.183	1.011
dh10	-0.436	0.478	-0.913	0.361	0.646	0.253	1.650
dh11	0.868	0.466	1.860	0.063	2.381	0.954	5.941
Pattern 1	-0.735	0.330	-2.227	0.026	0.479	0.251	0.916
Pattern 2	-0.244	0.262	-0.934	0.350	0.783	0.469	1.308
Pattern 3	-0.310	0.264	-1.176	0.240	0.733	0.437	1.230
Pattern 4	-0.404	0.287	-1.407	0.159	0.668	0.381	1.172
Pattern 6	-0.626	0.281	-2.231	0.026	0.535	0.308	0.927
Pattern 7	-0.759	0.251	-3.026	0.002	0.468	0.286	0.765
Pattern 8	-0.059	0.263	-0.224	0.823	0.943	0.563	1.578
Pattern 9	-0.227	0.236	-0.962	0.336	0.797	0.501	1.266
Pattern 10	0.005	0.243	0.022	0.982	1.005	0.624	1.620
dh7.pattern 3	1.491	0.543	2.747	0.006	4.439	1.532	12.860
dh9.pattern 3	1.535	0.775	1.979	0.048	4.641	1.015	21.219
dh11.pattern 3	1.719	0.955	1.801	0.072	5.581	0.859	36.259
dh8.pattern 4	1.524	0.577	2.644	0.008	4.593	1.483	14.220
dh10.pattern 4	1.731	1.232	1.405	0.160	5.643	0.504	63.132
dh7.pattern 5	1.147	0.509	2.251	0.024	3.148	1.160	8.544
dh6.pattern 7	1.639	0.454	3.612	0.000	5.148	2.116	12.528

AIC = 2,384.3

In Figure 16, the log odds for any predictor that is part of an interaction term is given by:

$$Ln[OR_i] = \beta_{dh\_i} \text{ x } dh_i + \beta_{c\_i} \text{ x } c_i + \beta_{ci\_dhi} \text{ x } c_i \text{ x } dh_i$$

Figure 16. Equation to Determine Log Odds for Any Predictor that is Part of an Interaction Term

One can observe that the effect of adding interaction terms is to increase the crash odds for particular driving time and multiday pattern combinations. All the parameter values for the interaction terms in Table 14 are positive, indicating an increase in crash odds. Several trends are apparent in the interaction terms in the model:

- Nearly all the interaction terms have long driving hours as one component. The interaction terms with pattern 3 include increased crash odds for driving times of 7, 9, and 11 hours. For pattern 4, driving times of 8 and 10 hours are significant as interactions. For pattern 5, driving 7 hours is significant. Pattern 7 has an interaction with 6 hours driving. While not apparent from analysis of the main effects alone, there now appears to be an association of driving time and crash odds for patterns 3, 4, and possibly 5.
- In addition, the sets of interactions for patterns 3, 4, and 5 place the long driving times as occurring in the late afternoon (a period of possible commuter congestion or increased traffic flow and thus increased odds of multivehicle crashes).
- The interaction for pattern 7 places the driver in the 6th hour during the dawn hours (4–6 a.m.), which is a period of known elevated crash odds.

Thus, each of the interactions increase crash odds and have ties to contexts in which crash odds increases are expected. The AIC with the interaction terms decreases from 2406.0 to 2,384.3. This decrease of more than 20 points shows that multiday driving patterns have an association with crash odds that are best considered through interaction effects.

4.1.6 Time of Day

An attempt was made to add specific variables describing the time of day of driving into the models as discussed in Section 3. When time of day is added, many parameters change magnitude by a small amount, but the AIC actually worsened, changing from 2,384.3 to 2,388.1 (see Table 15). The study team's judgment is that the effect of time of day is already addressed by the main effects and interactions of driving time and multiday patterns. Therefore, time of day was dropped as a predictor in subsequent models, as there is little need for an additional time-of-day variable.

4.1.7 Effect of driving break

Table 16 summarizes model results when one adds variables describing the presence of one, two, and three or more driving breaks during the trip of interest. The AIC (2,384.9) represents virtually no improvement in goodness of fit compared to the model in Figure 13. However, the parameters for the breaks show a reduction in crash odds of 32 percentage points with two breaks. The effects of taking one or three breaks are far from significance. While the overall goodness of fit does not improve, the interpretability of the model does, so subsequent models retain the three driving break variables.

Table 15. Crash Odds: Driving Time, Patterns, Interactions, and Time of Day—TL Drivers

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower CI	Upper CI
(Intercept)	-2.894	0.318	-9.098	0.000	n/a	n/a	n/a
dh2	-0.376	0.213	-1.764	0.078	0.687	0.452	1.043
dh3	-0.154	0.210	-0.734	0.463	0.857	0.568	1.293
dh4	-0.047	0.214	-0.218	0.827	0.954	0.627	1.452
dh5	-0.250	0.238	-1.050	0.294	0.779	0.488	1.242
dh6	-0.585	0.296	-1.974	0.048	0.557	0.312	0.996
dh7	-0.314	0.316	-0.993	0.321	0.731	0.394	1.357
dh8	0.047	0.296	0.158	0.874	1.048	0.586	1.873
dh9	-0.692	0.446	-1.553	0.120	0.501	0.209	1.199
dh10	-0.309	0.489	-0.633	0.527	0.734	0.281	1.914
dh11	1.032	0.478	2.161	0.031	2.807	1.101	7.157
Pattern 1	-0.803	0.337	-2.382	0.017	0.448	0.231	0.867
Pattern 2	-0.311	0.264	-1.175	0.240	0.733	0.436	1.231
Pattern 3	-0.392	0.268	-1.464	0.143	0.676	0.400	1.142
Pattern 4	-0.460	0.289	-1.590	0.112	0.631	0.358	1.113
Pattern 6	-0.554	0.291	-1.906	0.057	0.575	0.325	1.016
Pattern 7	-0.793	0.252	-3.143	0.002	0.453	0.276	0.742
Pattern 8	-0.106	0.272	-0.388	0.698	0.900	0.528	1.534
Pattern 9	-0.271	0.238	-1.138	0.255	0.763	0.478	1.216
Pattern 10	0.075	0.247	0.305	0.760	1.078	0.665	1.749
T_2	0.700	0.396	1.765	0.078	2.013	0.926	4.378
T_4	-0.060	0.444	-0.135	0.893	0.942	0.395	2.248
T_6	0.836	0.337	2.481	0.013	2.307	1.192	4.465
T_8	0.867	0.309	2.810	0.005	2.380	1.300	4.357
T_10	0.574	0.306	1.880	0.060	1.776	0.976	3.233
T_12	0.762	0.290	2.632	0.008	2.143	1.215	3.781
T_14	0.641	0.290	2.214	0.027	1.899	1.076	3.349
T_16	0.491	0.294	1.669	0.095	1.634	0.918	2.909
T_20	0.721	0.309	2.329	0.020	2.056	1.121	3.770
T_22	0.207	0.390	0.530	0.596	1.230	0.572	2.643
T_24	0.241	0.443	0.544	0.586	1.273	0.534	3.035
dh7:pattern 3	1.543	0.547	2.823	0.005	4.680	1.603	13.664
dh9:pattern 3	1.646	0.781	2.109	0.035	5.187	1.123	23.955
dh11:pattern 3	1.717	0.969	1.773	0.076	5.567	0.834	37.165
dh8:pattern 4	1.578	0.582	2.710	0.007	4.846	1.548	15.175
dh10:pattern 4	1.808	1.246	1.451	0.147	6.096	0.530	70.060
dh7:pattern 5	1.171	0.514	2.280	0.023	3.226	1.179	8.826
dh6:pattern 7	1.718	0.456	3.769	0.000	5.574	2.281	13.621

AIC = 2,388.1

Table 16. Crash Odds by Driving Time, Driving Pattern, Interactions, Driving Break—TL Drivers

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-2.187	0.223	-9.821	< 2e-16	n/a	n/a	n/a
dh2	-0.379	0.212	-1.791	0.073	0.685	0.452	1.036
dh3	-0.180	0.206	-0.874	0.382	0.835	0.557	1.251
dh4	-0.084	0.208	-0.403	0.687	0.920	0.611	1.383
dh5	-0.303	0.230	-1.316	0.188	0.738	0.470	1.160
dh6	-0.660	0.289	-2.282	0.022	0.517	0.293	0.911
dh7	-0.433	0.307	-1.411	0.158	0.648	0.355	1.183
dh8	-0.127	0.285	-0.444	0.657	0.881	0.503	1.541
dh9	-0.816	0.437	-1.867	0.062	0.442	0.188	1.042
dh10	-0.413	0.479	-0.863	0.388	0.662	0.259	1.691
dh11	0.886	0.468	1.893	0.058	2.426	0.969	6.075
Pattern 1	-0.778	0.334	-2.328	0.020	0.460	0.239	0.884
Pattern 2	-0.253	0.262	-0.967	0.334	0.776	0.464	1.297
Pattern 3	-0.335	0.266	-1.260	0.208	0.715	0.424	1.205
Pattern 4	-0.385	0.288	-1.338	0.181	0.680	0.387	1.196
Pattern 6	-0.668	0.284	-2.355	0.019	0.513	0.294	0.894
Pattern 7	-0.733	0.251	-2.915	0.004	0.481	0.294	0.786
Pattern 8	-0.093	0.265	-0.353	0.724	0.911	0.542	1.530
Pattern 9	-0.232	0.238	-0.978	0.328	0.793	0.497	1.263
Pattern 10	0.009	0.244	0.037	0.971	1.009	0.625	1.628
1 driving break	-0.074	0.158	-0.471	0.638	0.928	0.681	1.265
2 driving breaks	-0.397	0.183	-2.173	0.030	0.672	0.470	0.962
3+ driving breaks	-0.034	0.157	-0.215	0.830	0.967	0.710	1.316
dh7:pattern 3	1.500	0.543	2.760	0.006	4.480	1.545	12.997
dh9:pattern 3	1.517	0.776	1.954	0.051	4.558	0.995	20.870
dh11:pattern 3	1.719	0.957	1.796	0.072	5.580	0.855	36.413
dh8:pattern 4	1.575	0.578	2.724	0.006	4.833	1.556	15.013
dh10:pattern 4	1.910	1.238	1.543	0.123	6.750	0.596	76.396
dh7:pattern 5	1.137	0.510	2.229	0.026	3.117	1.147	8.470
dh6:pattern 7	1.647	0.454	3.627	0.000	5.191	2.132	12.641

AIC = 2,384.9

4.1.8 Effect of 34-hour or longer recovery period

Table 17 summarizes the effect of adding a variable for a recovery period of 34 hours or more and the joint consideration of a return from the recovery at day or night. This model shows virtually no improvement from the prior model: it has an AIC of 2,384.8. Crash odds increase 64 percent when one has a recovery and returns to a night shift; the highest crash odds increase compared to the baseline of no recovery and day driving. The recovery with a day return is a 31-percent increase in odds.

Table 17. Crash Odds by Driving Time, Driving Pattern, Interactions, Driving Break, and 34-Hour Recovery—TL

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-2.482	0.272	-9.130	0.000	n/a	n/a	n/a
dh2	-0.378	0.212	-1.780	0.074	0.685	0.453	1.038
dh3	-0.181	0.206	-0.880	0.380	0.834	0.557	1.250
dh4	-0.085	0.208	-0.410	0.682	0.918	0.610	1.381
dh5	-0.302	0.231	-1.310	0.190	0.739	0.470	1.162
dh6	-0.660	0.289	-2.280	0.022	0.517	0.293	0.911
dh7	-0.427	0.307	-1.390	0.165	0.653	0.357	1.192
dh8	-0.125	0.286	-0.440	0.662	0.883	0.504	1.545
dh9	-0.811	0.437	-1.850	0.064	0.445	0.189	1.048
dh10	-0.405	0.479	-0.850	0.397	0.667	0.261	1.705
dh11	0.892	0.469	1.900	0.057	2.440	0.974	6.113
Pattern 1	-0.886	0.343	-2.580	0.010	0.412	0.211	0.807
Pattern 2	-0.206	0.268	-0.770	0.441	0.814	0.481	1.375
Pattern 3	-0.363	0.267	-1.360	0.175	0.696	0.412	1.175
Pattern 4	-0.402	0.289	-1.390	0.164	0.669	0.380	1.178
Pattern 6	-0.724	0.288	-2.520	0.012	0.485	0.276	0.852
Pattern 7	-0.591	0.262	-2.250	0.024	0.554	0.331	0.926
Pattern 8	-0.226	0.278	-0.810	0.415	0.797	0.463	1.375
Pattern 9	-0.255	0.239	-1.070	0.285	0.775	0.485	1.237
Pattern 10	0.099	0.247	0.400	0.690	1.104	0.680	1.792
dh7:pattern 3	1.494	0.544	2.750	0.006	4.456	1.534	12.942
dh9:pattern 3	1.531	0.777	1.970	0.049	4.624	1.008	21.207
dh11:pattern 3	1.776	0.959	1.850	0.064	5.904	0.901	38.687
dh8:pattern 4	1.589	0.579	2.740	0.006	4.899	1.574	15.253
dh10:pattern 4	1.937	1.240	1.560	0.118	6.937	0.611	78.803
dh7:pattern 5	1.117	0.511	2.190	0.029	3.057	1.124	8.314
dh6:pattern 7	1.663	0.455	3.660	0.000	5.273	2.164	12.853
B12_1	-0.028	0.160	-0.180	0.861	0.972	0.711	1.330
B12_2	-0.388	0.184	-2.110	0.035	0.679	0.473	0.974
B12_3	-0.038	0.158	-0.240	0.811	0.963	0.707	1.312
34-hour recovery; return work at night	0.492	0.201	2.440	0.015	1.636	1.102	2.428
34-hour recovery with return work day	0.272	0.177	1.530	0.125	1.312	0.927	1.857
No 34-hour recovery; return to work at night	0.257	0.230	1.120	0.265	1.293	0.823	2.031

AIC = 2384.8

4.2 DATA ANALYSIS FOR LESS-THAN-TRUCKLOAD CARRIERS

The analysis for the LTL carriers follows a similar structure to the TL modeling as shown in Figure 2. Driving patterns are first derived for the LTL data, and then a series of time-dependent logistic regression models are estimated as follows:

- Driving time.
- Driving time and driving pattern.
- Exploring interactions between driving time and pattern by estimating a series of models, combining their results and consolidating their significant predictors into one model.
- Explore effect of driving breaks (comparing no break during a trip to one, two, and three or more breaks).
- Explore the presence of a 34-hour recovery period, constructing a model to compare combinations of the recovery and time of day when drivers return to work (either day or night).

4.2.1 Driving patterns

Table 18 shows the number of crash and non-crash observations and the relative risk for each LTL driving pattern. Pattern 4 is chosen as the baseline because it has the highest proportion of crashes in the LTL dataset. Pattern-4 and pattern-5 drivers have nearly equal crash risk (1.00 and 0.935 respectively). Patterns 7, 8, and 9 have relative risks of (0.80, 0.84 and 0.79, respectively). Pattern 2 has the lowest crash risk (0.52), while pattern 1, pattern 6, and pattern 10 also have relatively low crash risks (0.56, 0.62 and 0.56 respectively). These results are consistent with those for TL drivers, in that they support the general view that driving patterns over days prior to the day of interest (i.e., prior 7 days) are associated with differences in the relative risk of a crash on the 8th day.

Table 18. Crash Relative Risk for LTL Clusters

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

Additional information about each pattern is presented in Table 19 and Table 20, which summarize the on-duty/not-driving time and off-duty time for each day for each pattern. Notice that pattern 4, with the highest relative risk, has 2–3 hours of on-duty/not-driving time for days

1–5, but less than one for days 6–7. In contrast, off-duty hours rise sharply on days 6–7. These data indicate that drivers in pattern 4 drive substantial hours during days 1–5, are largely off duty on days 6–7, and return to higher crash relative risk on day 8. Pattern 5 (another high relative risk pattern) has little off-duty time during days 1–3, but almost 20 hours off duty on days 5 and 6. Each of the driving patterns is discussed individually in the subsequent paragraphs, using Table 19, Table 20, and graphical plots of Figure 17 to Figure 28 to aid in analysis.

Table 19. Average On-Duty/Not-Driving Time for Each LTL Driving Pattern

Driving Pattern	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	1.867	0.269	1.779	3.627	3.597	3.412	3.123
2	0.253	0.293	0.299	0.418	0.424	0.628	0.918
3	0.434	0.403	0.301	0.515	0.622	0.607	0.582
4	2.466	3.176	2.654	2.685	1.873	0.673	0.978
5	0.696	0.758	0.692	0.562	0.165	0.227	0.565
6	2.863	1.959	0.053	0.947	3.138	3.297	3.503
7	3.563	3.361	2.989	1.180	0.561	2.100	3.433
8	1.594	1.518	1.366	0.911	0.237	0.500	1.375
9	0.432	0.858	1.601	1.953	1.750	0.878	1.041
10	2.188	1.068	0.216	1.926	2.091	2.631	2.386

Table 20. Average Off-Duty Time for Each LTL Driving Pattern

Driving Pattern	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	18.805	22.321	17.367	12.334	12.519	13.091	14.636
2	16.887	18.369	19.070	17.643	13.034	11.226	10.872
3	16.719	17.617	17.990	14.842	12.821	12.230	13.929
4	14.503	13.238	13.259	13.864	16.546	20.926	20.022
5	8.981	8.054	8.815	14.008	19.973	19.646	12.919
6	14.194	17.841	23.534	20.222	13.350	12.391	12.109
7	12.630	12.891	15.002	20.676	21.580	16.202	12.628
8	12.946	12.594	13.777	16.871	21.482	20.540	14.522
9	19.595	16.601	11.622	12.000	12.027	16.149	18.007
10	12.398	17.665	22.307	17.926	14.068	12.125	11.818

Pattern 1 (Figure 17) has little on-duty or driving time in the first 3 days, but then very regular driving from around midnight at the end of day 3 until the end of day 7. In the discussion that follows, the authors refer to on-duty time for ease of exposition, but the time includes driving time and on-duty/not-driving time and is intended to be compared with the maximum cumulative hours of service of 70 hours in 8 days. While the proportion of drivers decreases somewhat from day 3–7 it is still 70 percent at midnight at the end of day 7. Off-duty time mirrors on-duty time

as there is minimal sleeper berth usage by drivers in this pattern. This driving pattern has the second lowest relative risk, 0.56.

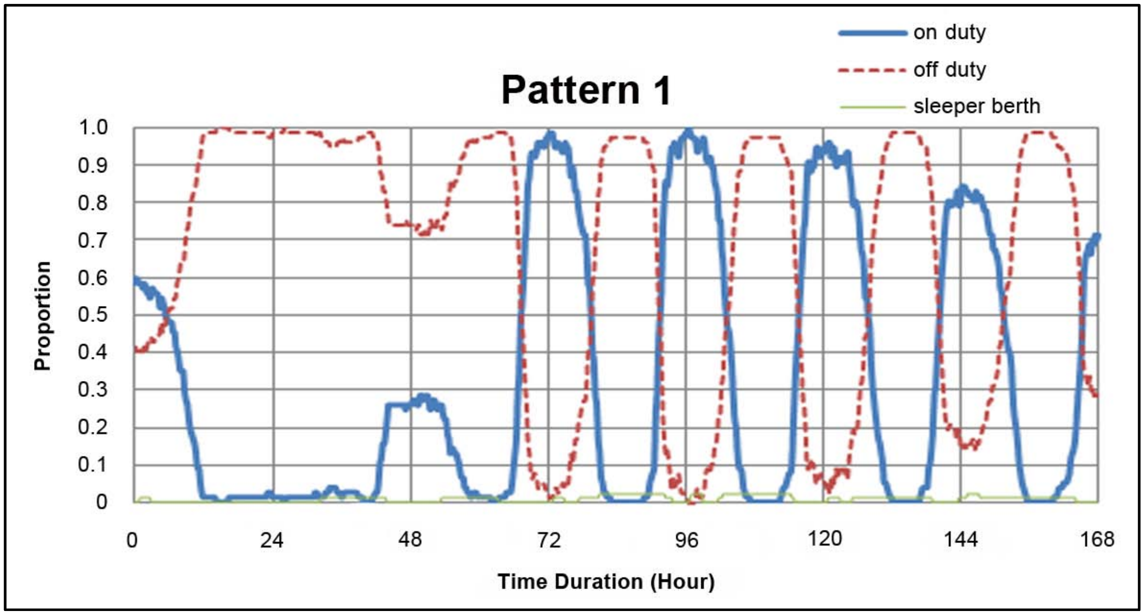


Figure 17. Summary of Multiday Driving Pattern 1—LTL Drivers

Pattern 2 (Figure 18) has the lowest relative risk of the 10 patterns (0.52). Drivers in this pattern are on duty infrequently during days 1–4, increasing their on-duty time during days 6, 7, and 8. On-duty time builds gradually from noon, and peaks at night around 10 p.m. So drivers in this cluster have their extended work hours (9, 10, and 11) during the early morning time. About 20 percent of drivers in this pattern use sleeper berths, particularly during days 5–7. In contrast to pattern 1 and many other patterns for LTL, this pattern is relatively irregular with high off-duty time on days 1–4—an observation supported by the values in Table 20 (off-duty time averaging 17–19 hours for the first 4 days).

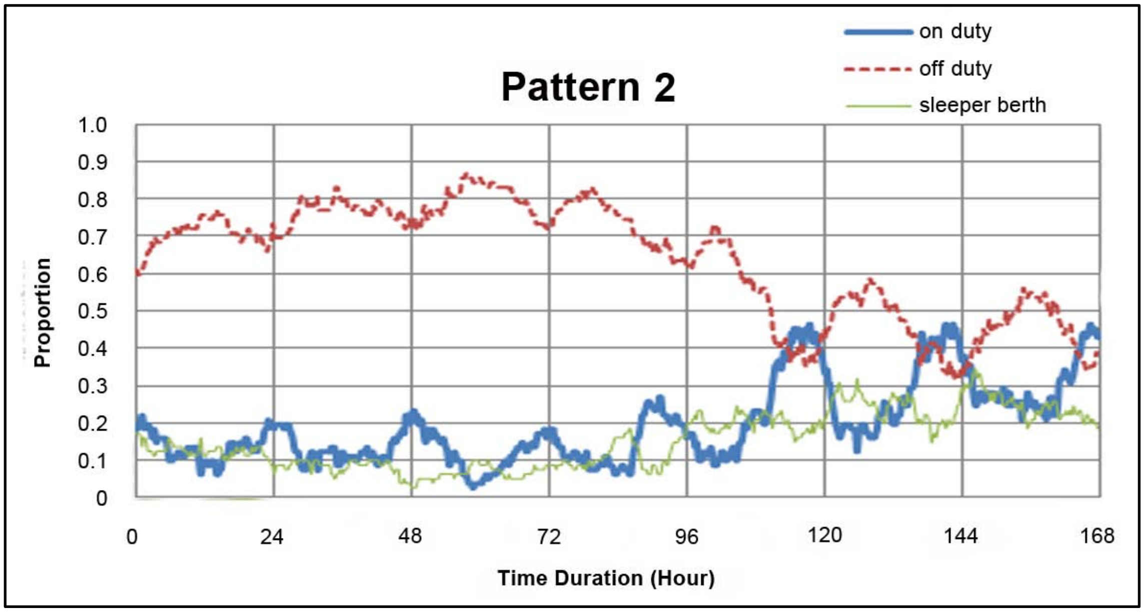


Figure 18. Summary of Multiday Driving Pattern 2—LTL Drivers

Pattern 3 (Figure 19) has somewhat irregular driving on days 1–4 with relatively few drivers on duty. Days 5–7 show most drivers scheduled with starting time in the morning, peaking at about 6 a.m. and ending in late afternoon, around 4–6 p.m. Sleeper berth use is low during days 1–4 but picks up to about 20 percent of drivers on days 5–7. The relative risk for this group is 0.69.

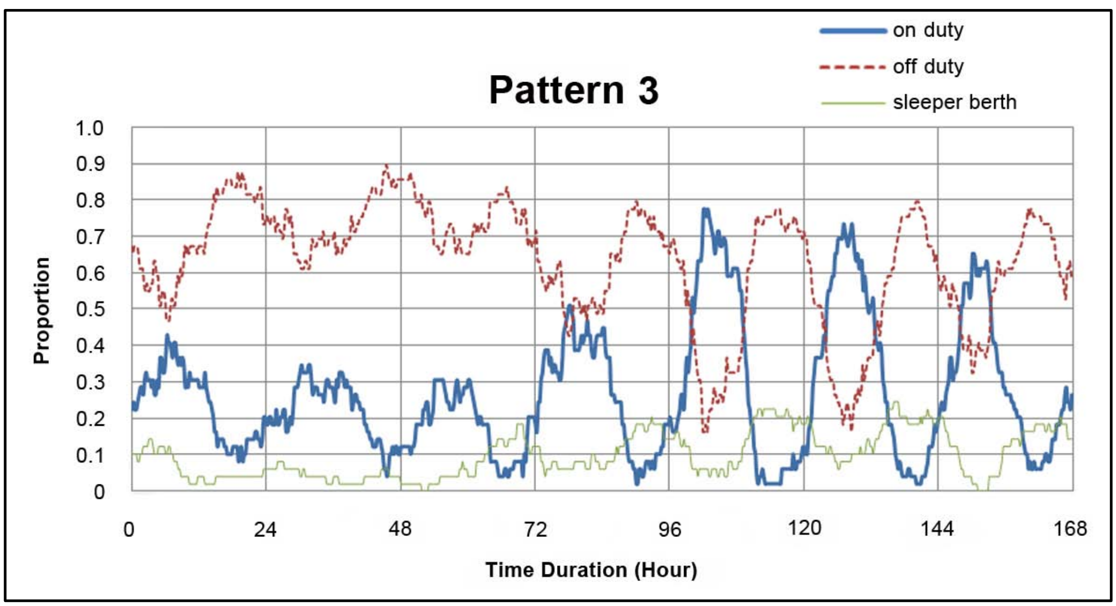


Figure 19. Summary of Multiday Driving Pattern 3—LTL Drivers

Pattern 4 (Figure 20) has the highest relative risk (1.00) and has very regular work time (particularly days 1–4) centered around 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. This pattern and its high relative risk is consistent with other pattern in the TL analyses that show a high relative risk when returning to work after 1–2 days off, particularly when returning at night. It is interesting to note that patterns 1 and 2 involve night driving, but have a low relative risk; it seems that it is the return to night driving after multiple days off that contributes to the high relative risk. Quantitative modeling using logistic regression (discussed in Section 4.2.4 and 4.2.5) should provide additional verification of this observation.

Pattern 5 (Figure 21) has fairly regular work scheduled during days 1–3, but then drops during day 4, with very few drivers working on days 5 and 6. These observations are verified by the high off-duty time for days 5 and 6 for this pattern in Table 20. Drivers are increasingly working through day 7 after about noon, but the pattern only shows 40 percent of drivers working at that time (40 percent are off duty and 20 percent in a sleeper berth). Off duty and sleeper berth use jump around in days 1–4, showing an irregular on-duty schedule. This pattern has a high relative risk (0.94). There is some consistency with pattern 4, in that drivers return to work at night after having several days off.

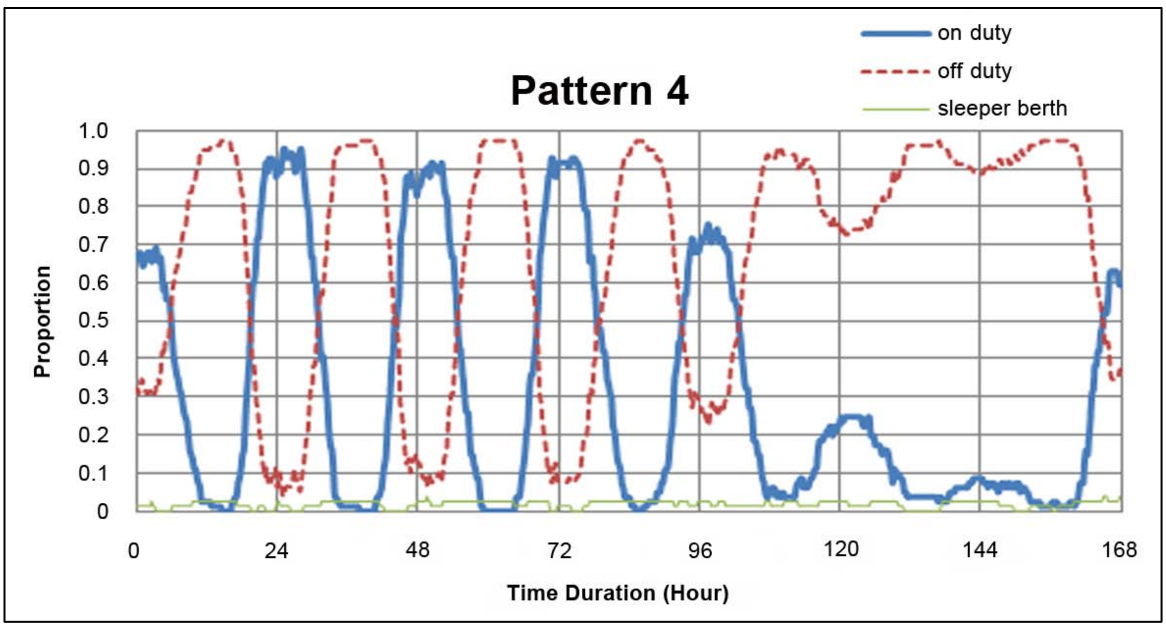


Figure 20. Summary of Multiday Driving Pattern 4—LTL Drivers

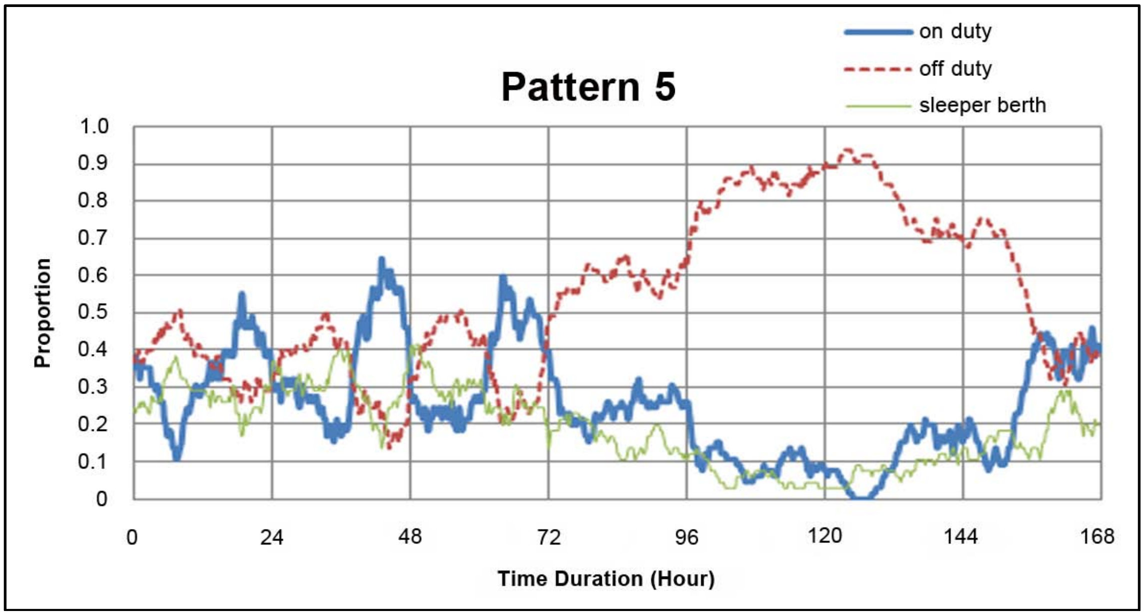


Figure 21. Summary of Multiday Driving Pattern 5—LTL Drivers

Pattern 6 (Figure 22) is a regular pattern with on-duty time centered around midnight, particularly at the beginning of day 1 and the end of day 4–7. The pattern is very regular, in that almost 100 percent of drivers are on duty around midnight and off duty around noon on the days when scheduled to work. There is little sleeper berth use by drivers; virtually all drivers are off duty from the end of day 2 to end of day 4. This pattern has moderate relative risk (0.62).

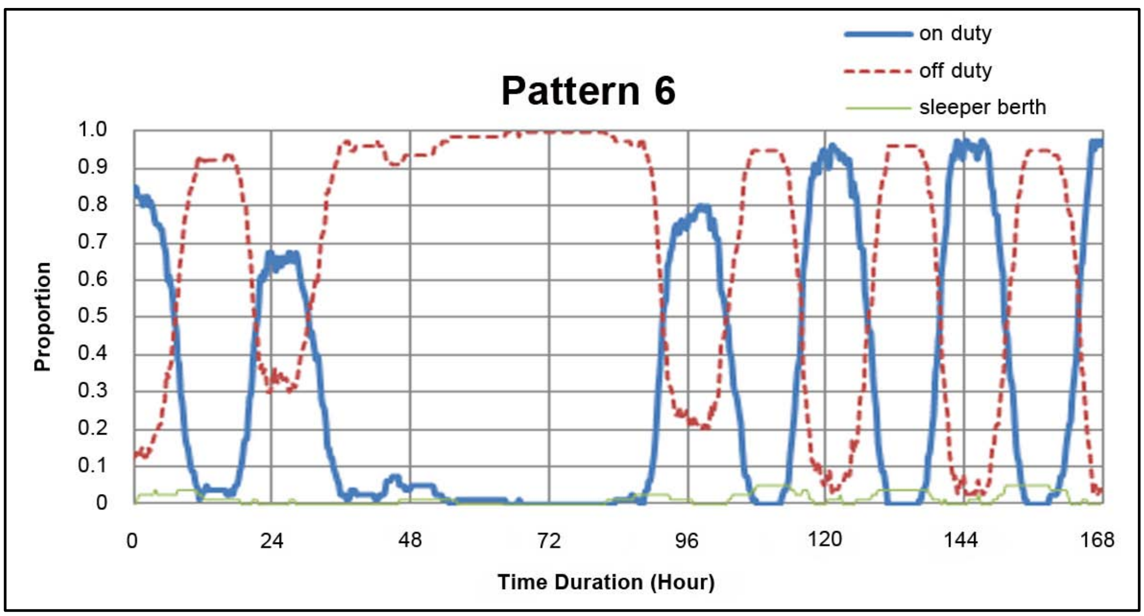


Figure 22. Summary of Multiday Driving Pattern 6—LTL Drivers

Pattern 7 (Figure 23) is another pattern that has work centered around midnight. In this case, at the beginning of day 1 and then again at the end of day 1, 2, 6, and 7. There is substantial (100 percent) off-duty time in midday on day 3, then again from midday on day 4 through the end of day 5. There is very little sleeper berth use by any driver in this pattern. There are some drivers working at the end of day 3 and 5 but only about 50 percent of those in the pattern. This pattern is ostensibly the same as pattern 1, 4, and 6, but captured at a different point in time. Pattern 7 has a moderately high crash relative risk (0.80).

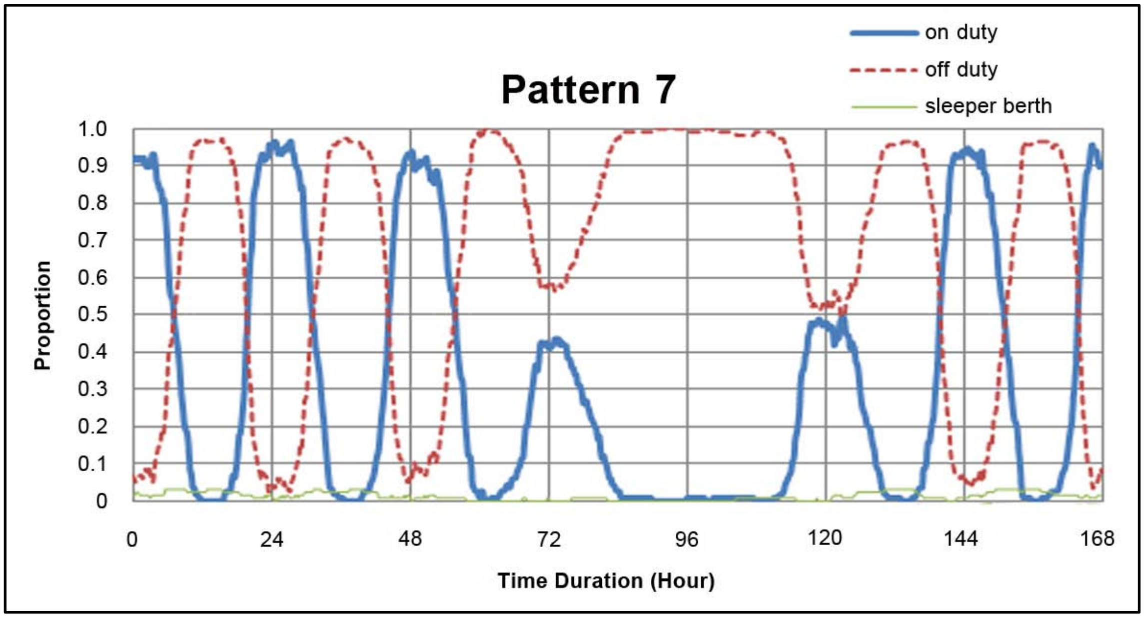


Figure 23. Summary of Multiday Driving Pattern 7—LTL Drivers

Pattern 8 (Figure 24) 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 very regular on days 1, 2, 3, and 7, and about 50 percent of the drivers work on day 4. Most drivers are off duty on days 5 and 6, and there is almost no sleeper berth use. This pattern has a moderately high crash relative risk (0.84).

Pattern 9 (Figure 25) is a rather mixed pattern. There is little work on day 1, but about 50 percent of the drivers in the pattern are working on day 2 clustered around 2 p.m. On days 3–5 drivers are scheduled regularly around 2 p.m., ending their shifts in the early morning. About 30–40 percent of drivers work on days 6 and 7, but centered around 2 p.m. Table 20 shows that this pattern has very high off-duty time for day 1 and 7 (19.6 and 18.0 hours, respectively) and moderate for days 2 and 6 (16 hours). This pattern has moderately high crash relative risk (0.79).

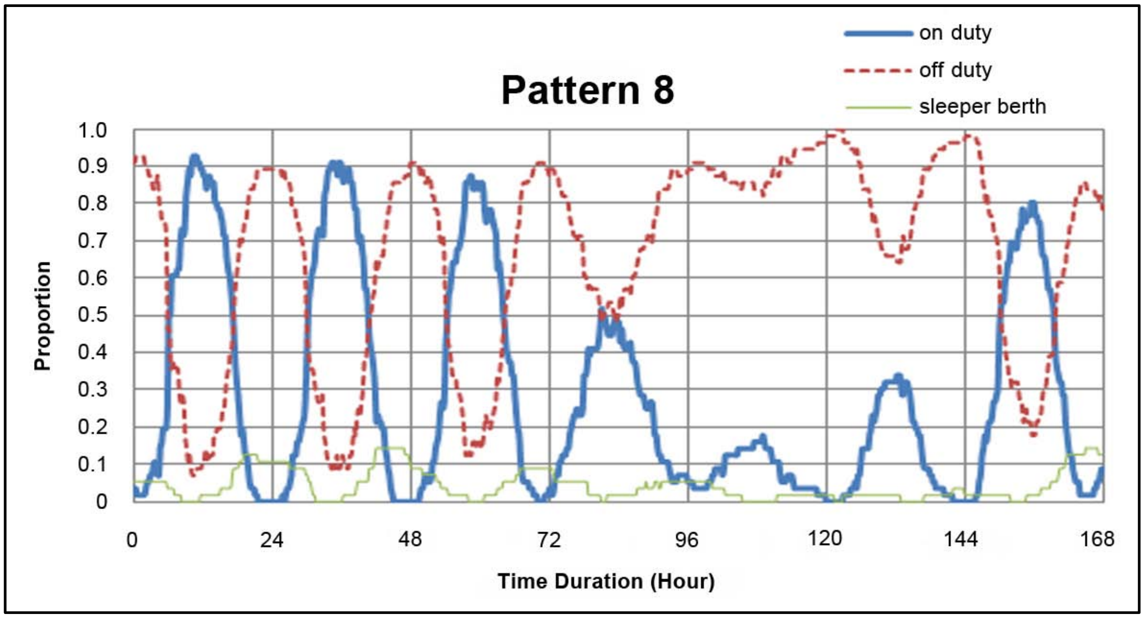


Figure 24. Summary of Multiday Driving Pattern 8—LTL Drivers

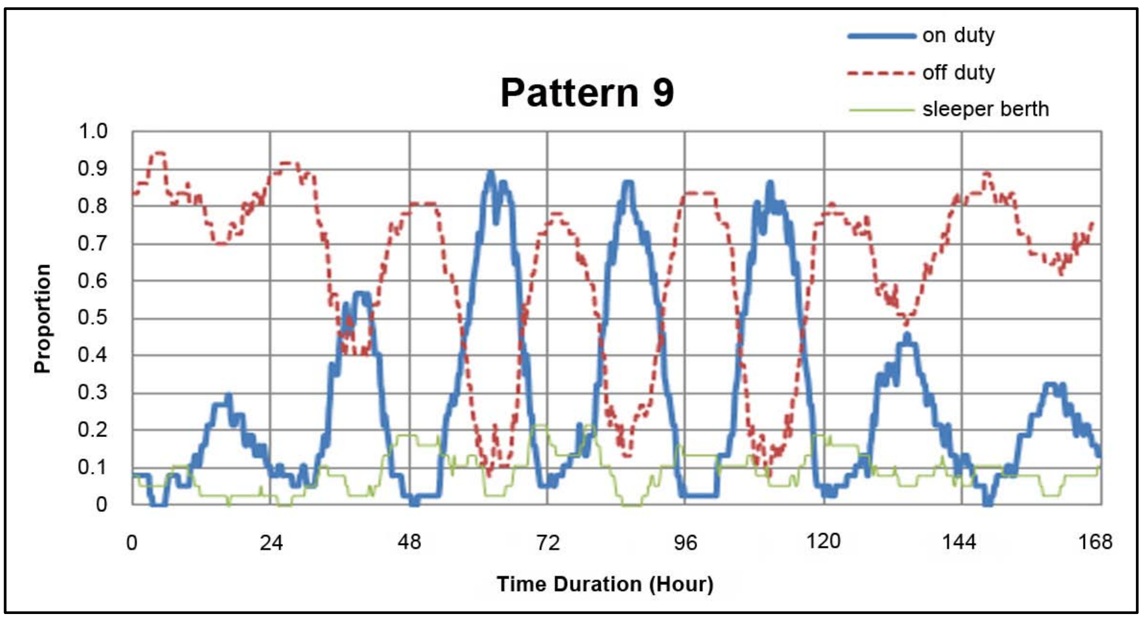


Figure 25. Summary of Multiday Driving Pattern 9—LTL Drivers

Pattern 10 (Figure 26) has regular work centered around noon, particularly for days 1, 5, 6, and 7. About 50 percent of the drivers work on days 2 and 4, and almost all are off duty on day 3. This pattern is very similar to patterns 8 and 9 and somewhat similar to pattern 3 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 risk (0.56).

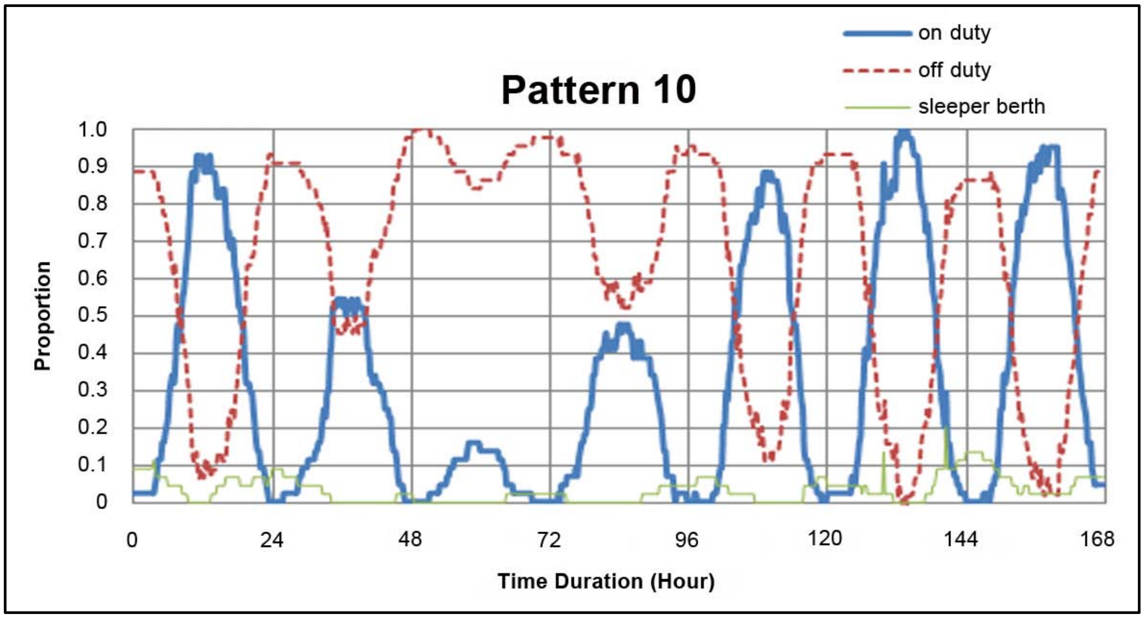
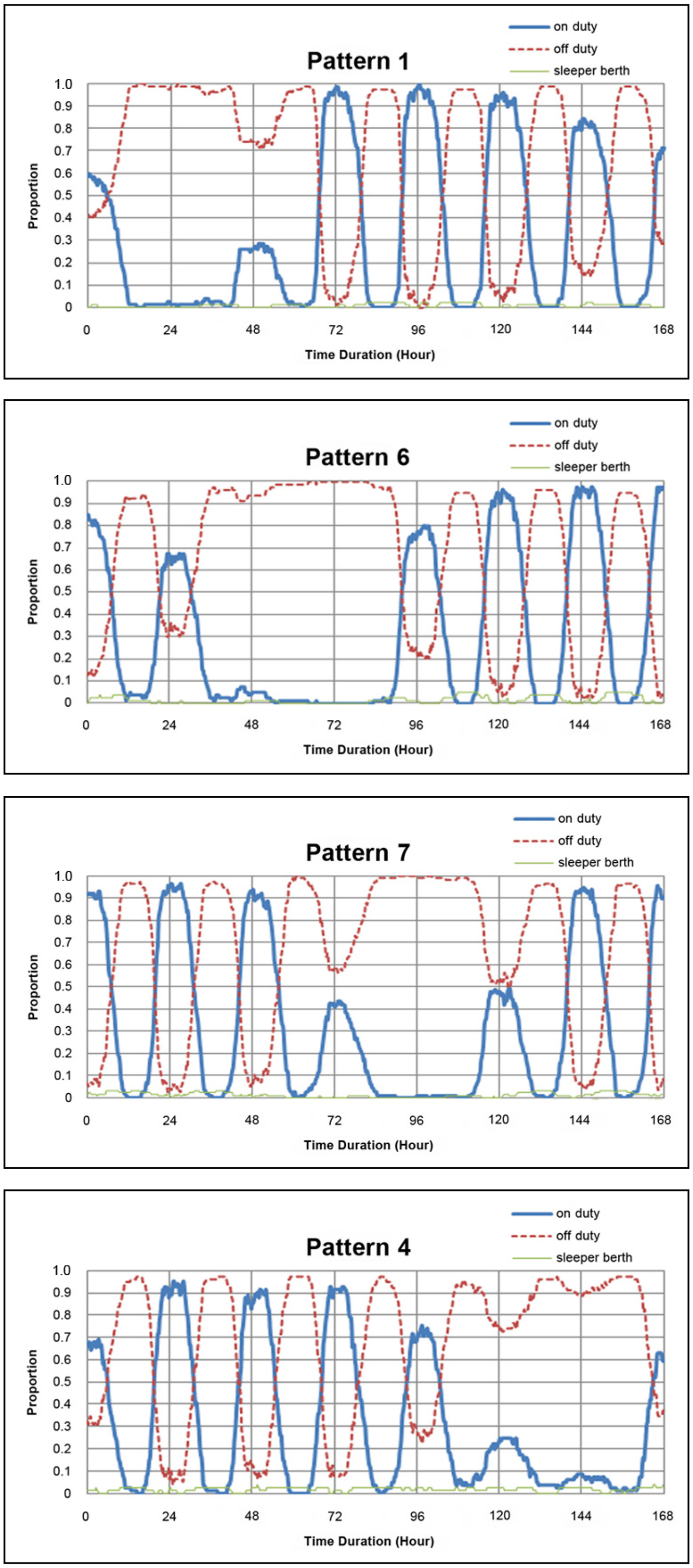


Figure 26. Summary of Multiday Driving Pattern 10—LTL Drivers

Additional insights concerning crash odds can be gleaned by arranging the multiday driving patterns in particular order. Figure 27 summarizes the multiday LTL patterns for drivers with regular late night and early morning driving schedules. From the figure, one can see the progression of the recovery period moving down the page. Each of the patterns is also associated with a relative crash risk as shown. Notice that the relative crash risk increases as the recovery period comes closer to the day of interest, starting at 0.56 when the recovery is on days 1 and 2, and increasing to when the recovery occurs on day 7. The study team interprets this finding as being consistent with previous crash-related research concerning hours of service: drivers have an increased odds of a crash when returning from a recovery period. As they drive more, the odds from this effect are reduced.



RR = 0.56

RR = 0.62

RR = 0.80

RR = 1.00

Figure 27. Summary of LTL Late Night and Early Morning Driving Patterns

While somewhat less convincing, Figure 28 shows a similar trend for LTL drivers scheduled during midday and early evening. The patterns are arranged with the recovery period moving from days 3 and 4 in pattern 10 at the top of the figure to days 7 and 1 in pattern 9 at the bottom of the figure. These patterns may thus be conceptualized as the same driving pattern but sampled at three different points in time. As with the drivers in Figure 27, the trend appears to be an increase in crash odds as the recovery period moves closer to the day of interest.

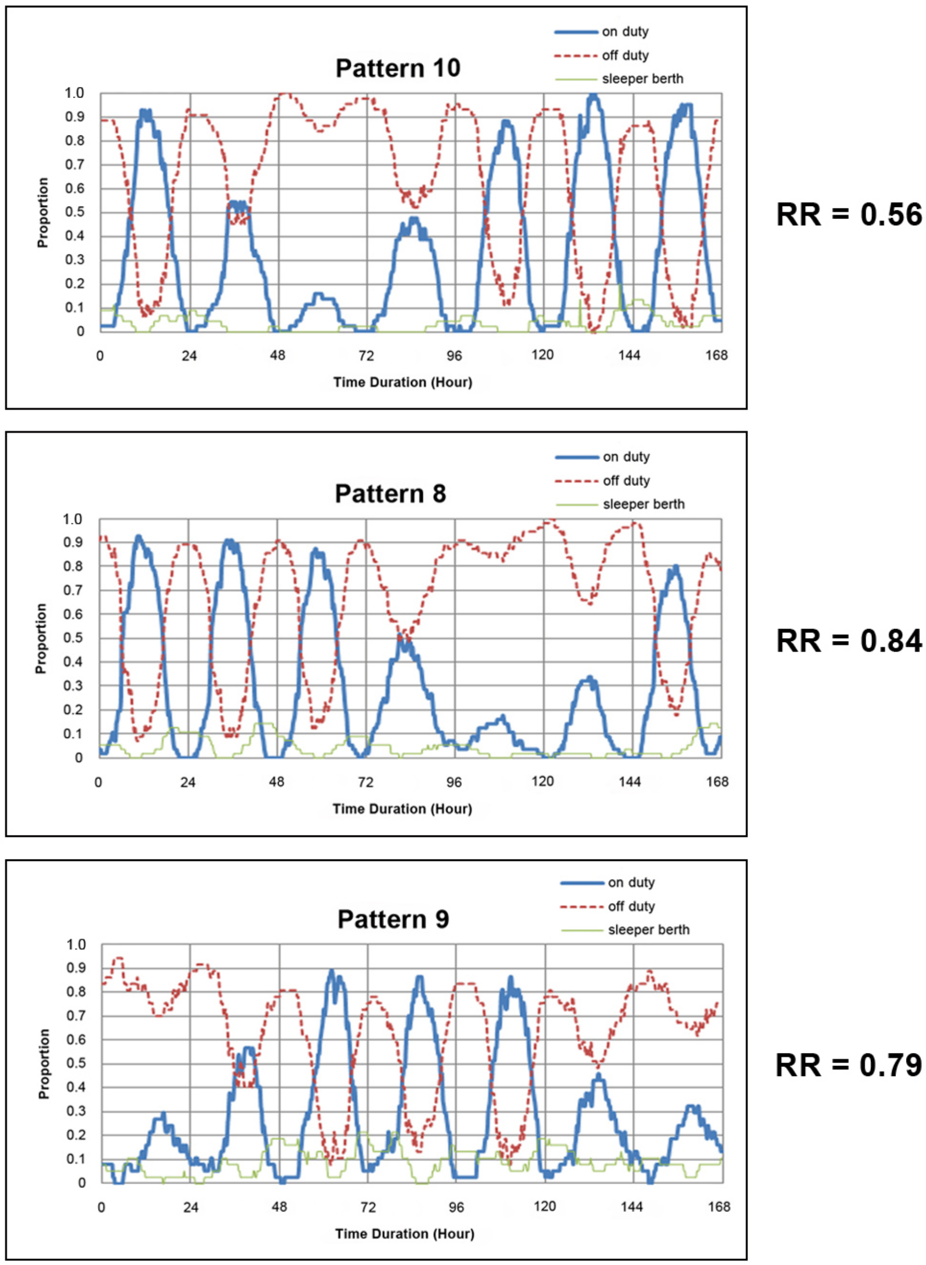


Figure 28. Summary of LTL Morning, Early Evening Driving Patterns

4.2.2 Time-dependent logistic regression models

The way testing of LTL data is conducted is similar to the testing of TL data using variables from Table 11.

4.2.3 Crash odds as function of driving time

Table 21 summarizes the results of the model estimating the probability of having a crash at time *t*, given survival until that time. Using the 1st hour as the baseline, there is an inability to detect a driving time effect for hours 3 and 4 (i.e., the level of significance is 0.98 and 0.44 respectively). The 2nd hour is barely lower than the 1st; the level of significance is 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 to hour 1 ($p = 0.12$) but it shows an increase in the crash odds of 63 percent (see column 6). Hours 6–11 show increases in the odds ratio; the odds ratio for each hour is greater than the previous hour. These results are consistent with previous studies of LTL carriers conducted with data from the 1980s (e.g., Lin et al., 1993; Lin et al., 1994; Park et al., 2005). The trend in crash odds ratios is shown in Figure 29; this figure shows a plot of the odds ratios from column 6 of Table 21. As the driving time increases, the odds ratio increases. Table 21 indicates that the confidence interval increases as well (reflecting the 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. As with all TL models in Section 4.1, all models for LTL pass a likelihood ratio test for significance as a whole compared to a model with a constant term only.

Some may ask if any particular driving hour is significantly different from any other hour (rather than focus on comparisons with the 1st hour only). It is possible to compare any driving time parameter with any other driving time parameter using a Wald test (Greene, 2003; Train, 2009; Cameron and Trivedi, 2010). The null hypothesis for the test is that the difference in the two parameter values is equal to zero, compared to a difference that is different from zero.

Table 21. Crash Odds as Function of Driving Time—LTL

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-3.555	0.233	-15.281	< 2e-16	n/a	n/a	n/a
dh2	-0.511	0.383	-1.336	0.182	0.600	0.283	1.270
dh3	-0.008	0.339	-0.025	0.980	0.992	0.511	1.926
dh4	-0.286	0.373	-0.766	0.444	0.751	0.362	1.561
dh5	0.486	0.316	1.541	0.123	1.626	0.876	3.019
dh6	0.722	0.311	2.325	0.020	2.059	1.120	3.785
dh7	0.974	0.304	3.202	0.001	2.649	1.459	4.808
dh8	1.351	0.298	4.533	0.000	3.862	2.153	6.927
dh9	1.655	0.306	5.404	0.000	5.232	2.871	9.535
dh10	1.895	0.342	5.544	0.000	6.650	3.404	12.992
dh11	3.188	0.492	6.478	0.000	24.231	9.236	63.571

AIC = 1,678.5

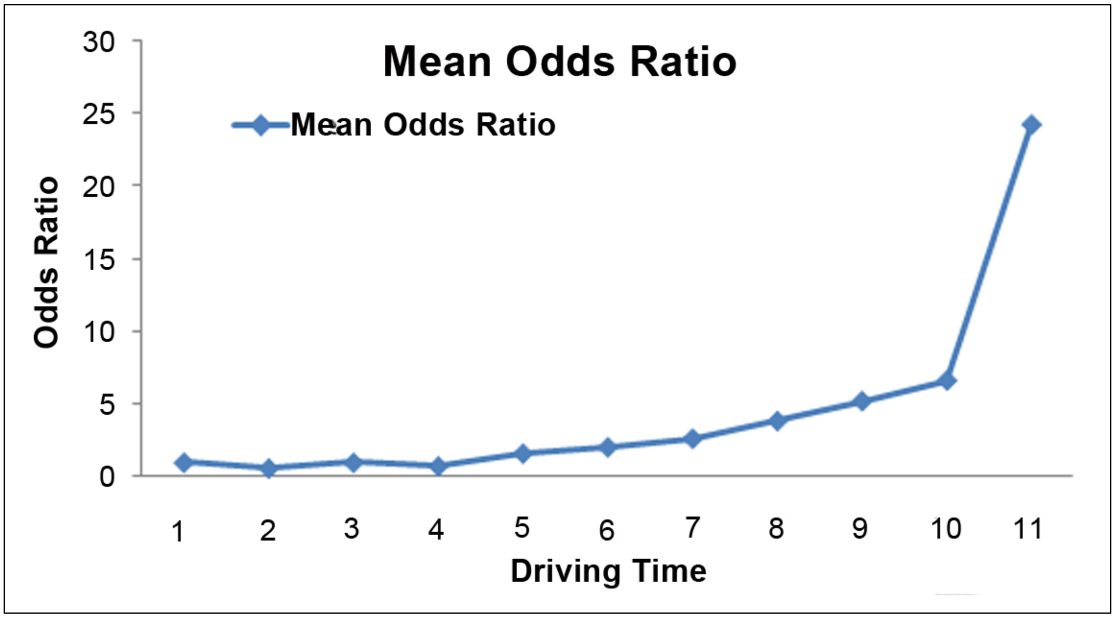


Figure 29. Trend in Crash Odds with Hours Driving—LTL

Table 22 summarizes the results of the comparisons of one hour with another. Both the horizontal and vertical scales indicate driving hours. The entries in the table are the test statistic value for the Wald test; the number in parentheses is the level of significance. As an example, consider the comparison of driving hours 6 and 7. The Wald statistic is 0.79 which yields a significance level of 0.38 (considered insignificant). One can therefore state: the Wald test was unable to find a difference between the parameters for the 6th and 7th hours of driving. Comparison of the column labeled "dh7" shows that hour 7 is significantly different from parameters for hours 1–5 (significance levels are 0.00 except for driving hour 5 which is 0.09). Examination of the columns of driving hours show that most of the tested differences are statistically "significant" (in this study, it means there is a level of significance greater than 0.20), except for the adjacent driving time.

Table 22. Summary of Hypothesis Test for Difference in Estimated Driving Time Parameters for LTL Drivers

Driving Time (Hrs.)	dh2	dh3	dh4	dh5	dh6	dh7	dh8	dh9	dh10	dh11
	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)
dh1	1.78 (0.18)	0.00 (0.98)	0.59 (0.44)	2.37 (0.12)	5.4 (0.02)	10.25 (0.00)	20.55 (0.00)	29.2 (0.00)	30.74 (0.00)	41.96 (0.00)
dh2		1.65 (0.20)	0.29 (0.59)	7.21 (0.01)	11.29 (0.00)	16.86 (0.00)	27.28 (0.00)	35.52 (0.00)	37.32 (0.00)	48.78 (0.00)
dh3			0.53 (0.477)	2.31 (0.13)	5.19 (0.02)	9.76 (0.00)	19.42 (0.00)	27.63 (0.00)	29.41 (0.00)	41.1 (0.00)
dh4				4.56 (0.03)	7.97 (0.001)	12.85 (0.00)	22.37 (0.00)	30.19 (0.00)	32.18 (0.00)	44.17 (0.00)
dh5					0.63 (0.43)	2.84 (0.09)	9.33 (0.00)	16.04 (0.00)	18.34 (0.00)	31.25 (0.00)
dh6						0.79 (0.38)	5.14 (0.02)	10.61 (0.00)	13.09 (0.00)	26.38 (0.00)
dh7							1.95 (0.16)	5.94 (0.02)	8.39 (0.00)	21.64 (0.00)
dh8								1.24 (0.27)	3.03 (0.08)	15.14 (0.00)
dh9									0.56 (0.45)	10.32 (0.00)
dh10										6.67 (0.01)

4.2.4 Crash odds as function of driving time and multiday driving pattern

The multiday driving patterns were next entered as main effects in the model. The results are shown in Table 23. There were minimal changes in the trends in parameters of driving time when the multiday patterns were entered. Most parameters increased slightly in magnitude, but this is not surprising given the negative signs of most of the multiday pattern parameters. The clear trend of increasing crash odds with increasing driving time is retained.

The odds ratios for the driving patterns generally tracked the computation of relative risk in Table 18. Pattern 4 is used again as the baseline and patterns 1–3, 6, 8, 9, and 10 all show significant or marginally significant differences from pattern 4. Patterns 5 and 7 have parameters unable to be differentiated from pattern 4. The basic interpretation that was developed in the discussion of these patterns in Section 4.2.1 is, the study team believes, still valid. There remains a concern about drivers returning to work after their long off-duty period of a day or more, particularly when they return to a night shift. The goodness of fit improves from 1,678.5 to 1,663.7, an improvement larger than the rule of thumb for significance.

Table 23. Crash Odds as Function of Driving Time and Multiday Pattern—LTL

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-3.064	0.282	-10.878	< 2e-16	n/a	n/a	n/a
dh2	-0.512	0.383	-1.334	0.182	0.600	0.283	1.271
dh3	0.000	0.339	0.000	1.000	1.000	0.514	1.944
dh4	-0.272	0.374	-0.728	0.467	0.762	0.366	1.585
dh5	0.517	0.317	1.632	0.103	1.677	0.901	3.118
dh6	0.784	0.312	2.516	0.012	2.191	1.189	4.037
dh7	1.047	0.306	3.427	0.001	2.849	1.565	5.186
dh8	1.431	0.300	4.771	0.000	4.183	2.324	7.528
dh9	1.770	0.309	5.729	0.000	5.871	3.204	10.756
dh10	2.079	0.346	6.002	0.000	7.996	4.055	15.767
dh11	3.398	0.504	6.737	0.000	29.904	11.127	80.369
Pattern 1	-1.175	0.298	-3.948	0.000	0.309	0.172	0.553
Pattern 2	-0.841	0.297	-2.830	0.005	0.431	0.241	0.772
Pattern 3	-0.539	0.323	-1.672	0.095	0.583	0.310	1.097
Pattern 5	-0.147	0.273	-0.538	0.591	0.864	0.506	1.473
Pattern 6	-0.812	0.288	-2.816	0.005	0.444	0.252	0.781
Pattern 7	-0.214	0.243	-0.880	0.379	0.808	0.502	1.300
Pattern 8	-0.447	0.291	-1.535	0.125	0.640	0.362	1.131
Pattern 9	-0.600	0.342	-1.757	0.079	0.549	0.281	1.072
Pattern 10	-1.245	0.362	-3.437	0.001	0.288	0.142	0.586

AIC = 1663.7

4.2.5 Crash odds as function of driving time, driving pattern, and interactions

Interaction terms are added to the previous model using the same technique as for the TL models: each driving hour was, in turn, tested for significant interaction terms with the driving pattern. The significant interactions were retained and after all driving hours were tested were then entered into a common model. Insignificant interactions were dropped, leaving the four significant interactions in Table 24.

Table 24. Crash Odds as Function of Driving Time, Driving Pattern, and Interactions—LTL

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-3.077	0.289	-10.662	< 2e-16	n/a	n/a	n/a
dh2	-0.795	0.426	-1.866	0.062	0.452	0.196	1.041
dh3	-0.002	0.339	-0.005	0.996	0.998	0.514	1.941
dh4	-0.274	0.374	-0.732	0.464	0.761	0.366	1.583
dh5	0.514	0.317	1.622	0.105	1.671	0.899	3.109
dh6	0.509	0.349	1.459	0.144	1.664	0.840	3.299
dh7	0.861	0.322	2.672	0.008	2.367	1.258	4.452
dh8	1.422	0.300	4.742	0.000	4.146	2.303	7.462
dh9	1.762	0.309	5.701	0.000	5.822	3.177	10.667
dh10	1.856	0.375	4.950	0.000	6.395	3.067	13.334
dh11	3.367	0.504	6.681	0.000	29.002	10.799	77.890
Pattern 1	-1.070	0.306	-3.491	0.000	0.343	0.188	0.626
Pattern 2	-1.017	0.346	-2.943	0.003	0.362	0.184	0.712
Pattern 3	-0.437	0.330	-1.324	0.186	0.646	0.338	1.234
Pattern 5	-0.051	0.281	-0.181	0.856	0.950	0.548	1.649
Pattern 6	-0.710	0.297	-2.389	0.017	0.492	0.275	0.880
Pattern 7	-0.282	0.268	-1.053	0.292	0.754	0.446	1.275
Pattern 8	-0.350	0.299	-1.170	0.242	0.705	0.392	1.267
Pattern 9	-0.752	0.382	-1.967	0.049	0.471	0.223	0.997
Pattern 10	-1.141	0.370	-3.084	0.002	0.319	0.155	0.660
dh7:pattern 2	1.361	0.574	2.370	0.018	3.899	1.265	12.015
dh10:pattern 4	1.445	0.760	1.901	0.057	4.240	0.956	18.799
dh6:pattern 7	1.076	0.488	2.208	0.027	2.934	1.128	7.630
dh2:pattern 9	2.288	0.779	2.936	0.003	9.858	2.139	45.427

AIC = 1,651.0

The effect of the interactions is to increase crash odds but the effects are less systematic than for the TL models. Here, four different patterns are affected and with different lengths of driving time. However there are a few observations that can be made about the interactions. The first and third listed interactions result in increases in crash risk for driving near 6 a.m. This has been shown in previous studies to be a time of low circadian activity and elevated crash occurrence. The second interaction term (between hour 10 and pattern 4) results in driving near noon, when other traffic levels may be high in some areas due to midday travel. The last interaction term results in higher crash odds when driving near 4–5 p.m. This is another possible time of increased traffic and/or low circadian rhythms for some. So the interaction terms in this model are not correcting for the effect of extended time on task; they are instead picking up possible circadian or traffic-related effects.

The use of the interaction terms decreases the AIC from 1,663.7 to 1,651.0, another substantial decrease. There is thus strong evidence that the addition of the interaction terms substantially improved model fit.

4.2.6 Crash odds as function of driving time, driving pattern, interactions, and driving breaks

A set of three variables were added to the previous model to test for the effect of breaks from driving. The variables represented taking one, two, or three or more breaks from a baseline of no breaks. All the breaks result in estimated reductions in crash odds, but only taking two breaks results in statistical significance.

The goodness of fit only improves from 1,651.0 to 1,650.5 an insignificant overall improvement. Most of the existing parameter values change little with the added variables, indicating that the effect appears to be across the board for all driving time and patterns. The model is shown in Appendix A (Table 30) because the change in model parameters and goodness of fit was so small.

4.2.7 Crash odds as function of driving time, pattern, interactions, driving breaks, and interactions of 34-hour recovery and time of day of return to duty

Separate models were estimated for the effect of the 34-hour recovery and night driving (on the trip of interest). These did not improve model fit or interpretation and are not reported. The last model combines these two concepts by adding variables representing the interaction of the 34-hour recovery and night return to duty immediately thereafter. The baseline is no recovery and a daytime trip. Dummy variables represent a 34-hour recovery with a night return to duty, a 34-hour recovery with a day return to duty and a night trip without a recovery. These four dummy variables and all other predictors from the model are summarized in Table 25.

The parameter values for the new interaction term indicate increased odds for all three dummy variables, but particularly for drivers returning during the day. This is different than the results obtained from the TL analysis. Other parameter values changed little except for pattern 2 and pattern 8 main effects which both increased (i.e., the crash odds increased for drivers in this multiday pattern). There was not a clear rationale for this result.

The model in Table 25 fits substantially better than the one in Table 30. The AIC improved to 1,644.3 from 1,650.5.

Table 25. Crash Odds as Function of Driving Time, Pattern, Interactions, Driving Breaks, and Interactions of 34-Hour Recovery and Time-of-Day-of-Return—LTL

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-3.445	0.368	-9.355	< 2e-16	n/a	n/a	n/a
dh2	-0.791	0.426	-1.855	0.064	0.454	0.197	1.046
dh3	0.013	0.340	0.037	0.970	1.013	0.520	1.971
dh4	-0.250	0.374	-0.667	0.505	0.779	0.374	1.623
dh5	0.557	0.318	1.752	0.080	1.745	0.936	3.252
dh6	0.572	0.351	1.631	0.103	1.772	0.891	3.526
dh7	0.929	0.325	2.859	0.004	2.531	1.339	4.784
dh8	1.484	0.302	4.912	0.000	4.411	2.440	7.976
dh9	1.833	0.312	5.873	0.000	6.252	3.391	11.526
dh10	1.962	0.378	5.191	0.000	7.114	3.391	14.925
dh11	3.540	0.510	6.939	0.000	34.471	12.681	93.701
Pattern 1	-1.151	0.335	-3.440	0.001	0.316	0.164	0.609
Pattern 2	-0.866	0.370	-2.342	0.019	0.421	0.204	0.868
Pattern 3	-0.567	0.354	-1.602	0.109	0.567	0.283	1.135
Pattern 5	0.021	0.302	0.068	0.946	1.021	0.564	1.846
Pattern 6	-0.717	0.331	-2.167	0.030	0.488	0.255	0.934
Pattern 7	-0.336	0.299	-1.123	0.261	0.715	0.398	1.284
Pattern 8	-0.263	0.336	-0.782	0.434	0.769	0.398	1.486
Pattern 9	-0.945	0.426	-2.216	0.027	0.389	0.169	0.896
Pattern 10	-0.962	0.410	-2.345	0.019	0.382	0.171	0.854
numbreak12_1	-0.169	0.162	-1.044	0.296	0.845	0.615	1.160
numbreak12_2	-0.719	0.280	-2.572	0.010	0.487	0.282	0.843
numbreak12_3	-0.089	0.111	-0.803	0.422	0.915	0.736	1.137
dh7:pattern 2	1.366	0.578	2.363	0.018	3.920	1.262	12.172
dh10:pattern 4	1.567	0.774	2.025	0.043	4.793	1.052	21.842
dh6:pattern 7	1.079	0.489	2.205	0.027	2.941	1.127	7.671
dh2:pattern 9	2.301	0.784	2.935	0.003	9.983	2.148	46.400
34-hour recovery; return to work at night	0.458	0.281	1.628	0.103	1.581	0.911	2.743
34-hour recovery with return to work during day	0.926	0.292	3.169	0.002	2.523	1.424	4.473
No 34-hour recovery; return to work at night	0.561	0.217	2.590	0.010	1.753	1.146	2.681

AIC = 1,644.3

4.3 34-HOUR RESTART MODELS

Table 26 summarizes the results of the detailed analysis of the 34-hour restart policy. While there are only seven parameters in the model, they need to be interpreted with particular care. This model reflects the experience of only one carrier from 2010 and only the crash-involved drivers from that carrier. Section 3.9 contains a description of the rationale for this particular approach. In particular, the model compares crash-involved drivers to themselves (thus this is a "random effects" formulation). So an odds ratio greater than 1.0 means that the variable in question increases the odds of a crash for an individual driver.

The series of three predictors beginning with "pseudo" are coded as "1" if the driver *would have* violated the cumulative hours provision (i.e., 70 hours in 8 days) had the restart policy not been in place. The last number in each variable name refers to the number of days prior to the day of the crash trip: a 1 means the "pseudo-violation" occurred on the day before the crash trip; a 2 means 2 days before the crash day; a 3 implies 3 days before. The study team wants to emphasize that an HOS violation did not occur. What they were seeking was an indicator of the intensity of driving under the current regulations that would not have been permitted under the previous regulations. The additional predictors with two numbers after the "pseudo-violation" convey that the "pseudo-event" occurred for 2 consecutive days prior to the crash day. That is, either days 1 and 2 or days 2 and 3. As defined, one would associate more intense driving with either of these two parameters being set to "1."

The remaining predictors are simple indicator variables. "Night" is "1" if the crash trip starts at night (after 6 p.m.). "Recovery" is "1" if a 34-hour recovery period immediately preceded the crash trip.

The estimated model reveals that night conditions pose a near tripling of the odds of a crash compared to the same driver operating on different days. The recovery variable is even stronger in the opposite direction, illustrating a more than triple reduction of the crash odds when a recovery period immediately precedes the crash trip. While the night finding is generally consistent with other models in this report, the finding concerning recovery is very different. While the study team cannot be sure about the reasons for the difference, it is speculated that this analysis only involved crash drivers (not the safest drivers) and that they were compared to themselves, not others. In this context one can reasonably expect some differences in parameter values compared to models characterized as "between subjects."

The other five variables offer insights concerning the relationship of extended hours on duty and crash odds. "Pseudo-violations" which occur on either of the 2 days prior to the crash day (i.e., pseudo-violation 1 and 2) cannot be differentiated from no-effect (the significance probability, p, is greater than the 0.20 level chosen for this study). When the "pseudo-violation" occurs 3 days prior to the crash day, there is a barely detectable *decrease* in crash odds. Taken as a whole, these predictors indicate that an individual violation for 1 day is not strongly associated with a crash.

When the pseudo-violation occurs over 2 consecutive days, the odds ratios become greater than 1.00, indicating an increase in crash odds. The pseudo-violate12 variable is below significance for this research, but the occurrence of pseudo-violations 2 and 3 days before the crash days are associated with the crash and the effect is the largest in the model (a quadrupling of the odds). This implies that schedules that are compressed over 2 days are associated with increased crash odds on subsequent days. Compressed schedules over 1 day (i.e., the pseudo-violation variables being "1" for only 1 day) are not associated with increased crash odds. Additional research is needed to gain confidence in this formulation. Similar formulations can be used to explore whether this finding can be applied to other carriers.

Table 26. Crash Odds for One Carrier Using Fixed-Effect Case-Control for 34-Hour Restart

Coefficient	Estimate	Standard Error	Z value	P>(|z|)	Odds Ratio	Odds Ratio 95% CI	
Night	1.01	0.33	3.34	0.00	3.00	1.57	5.71
Pseudo-violate1	-0.08	0.67	-0.12	0.90	0.92	0.25	3.43
Pseudo-violate2	-0.84	1.04	-0.81	0.42	0.43	0.06	3.29
Pseudo-violate3	-0.85	0.65	-1.30	0.19	0.43	0.12	1.54
Pseudo-violate12	0.22	1.16	0.19	0.85	1.25	0.13	12.17
Pseudo-violate23	1.69	1.01	1.68	0.09	5.39	0.75	38.71
Recovery	-1.14	0.32	-3.53	0.00	0.32	0.17	0.60
Conditional fixed-effects logistic regression							
Log likelihood = -133.63091							
LR $chi^2(7)$ = 33.54							
Probability > chi^2 = 0.0000							
Number of observations = 427							
Number of groups = 131							

4.4 AGGREGATE MODEL WITH ALL DATA INCLUDED

While the testing of the data led to a decision to split the data between TL and LTL carriers, there was an interest in building a model with all the data (i.e., an aggregate model combining TL and LTL). Table 27 responds to the request for an aggregate model. It includes all the predictors used previously, except the multiday driving patterns, which were derived specifically from each dataset and could not be properly included in a model with all the data combined. In addition, the presence of a 34-hour or greater recovery period was simply defined with a dichotomous variable, not a series of interaction terms.

Table 27 shows that driving in hours 3–6 has a crash odds that cannot be distinguished from the 1st hour (i.e., all the levels of significance in column 5 of Table 27 are greater than 0.30). The 2nd hour shows a 34-percent drop (column 6) in odds which is significant. Crash odds are significant (compared to hour 1) and generally increasing for driving hours 7 or more. The association with increased driving time is similar to the relationship for LTL, but does not start until the 8th hour instead of the 5th or 6th. There is a 30-percent reduction in crash odds with two driving breaks (column 6, variable B12_2). A recovery period of 34 hours or longer is associated with a 50-percent increase in the odds of a crash on the 1st day back compared to a return to work with no recovery. Figure 30 is a graphical depiction of the effect of driving time on crash odds.

Table 27. Aggregate Model with TL and LTL Data Combined

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-3.096	0.138	-22.370	0.000	n/a	n/a	n/a
dh2	-0.417	0.184	-2.270	0.023	0.659	0.459	0.945
dh3	-0.152	0.175	-0.870	0.384	0.859	0.610	1.210
dh4	-0.161	0.180	-0.900	0.371	0.851	0.598	1.211
dh5	-0.057	0.181	-0.310	0.754	0.945	0.662	1.348
dh6	0.081	0.182	0.450	0.656	1.085	0.759	1.550
dh7	0.360	0.178	2.030	0.043	1.434	1.012	2.032
dh8	0.607	0.181	3.350	0.001	1.835	1.286	2.617
dh9	0.593	0.204	2.910	0.004	1.810	1.213	2.699
dh10	0.847	0.241	3.520	0.000	2.332	1.454	3.738
dh11	1.913	0.301	6.360	0.000	6.774	3.756	12.215
B12_1	0.004	0.107	0.040	0.971	1.004	0.814	1.239
B12_2	-0.333	0.141	-2.350	0.019	0.717	0.544	0.946
B12_3	0.019	0.074	0.260	0.795	1.019	0.882	1.179
Recovery	0.416	0.090	4.610	0.000	1.517	1.270	1.811

In order the better understand differences in the crash odds ratios across driving time, a series of Wald tests were conducted for differences in the parameters values for driving time. The null hypothesis for the test is that the difference in the estimated value for any pair of parameters is indistinguishable from zero. Table 28 summarizes the results of the series of Wald tests. Within each cell of the table, the top number is the value of the Wald test statistic; the number in parentheses is the value for the level of significance.

Notice that driving hours 3–6 are generally not different from each other. This can be found by examining the column labeled dh6 and seeing that the cells intersecting with dh3–dh5 contain test statistic values less than 2 and significance probabilities greater than 0.2. Driving hour 2 is the only one of the first 6 that is different. It is barely different from hour 3 and 4 (level of significance of 0.17 and 0.20, respectively). Among the other findings of the hypothesis test results shown in the table are:

- The 11th hour is different than all other hours.
- The 10th hour cannot be differentiated from hour 8 and 9, but it is greater than hours 7 and 6 and all others back to driving hour 1.
- The 9th hour cannot be differentiated from 8 and 7, but is greater than all the other driving hours (i.e., 6 or less).

The results of the tests generally support the concept that the crash odds increase as driving time increases.

Table 28. Wald Test for the Aggregate Model

Driving Time (Hours)	dh2	dh3	dh4	dh5	dh6	dh7	dh8	dh9	dh10	dh11
	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)	Chi^2 (p)
dh1	5.15 (0.02)	0.76 (0.38)	0.81 (0.37)	0.10 (0.76)	0.20 (0.66)	4.12 (0.04)	11.16 (0.00)	8.53 (0.00)	12.46 (0.00)	40.83 (0.00)
dh2		1.84 (0.17)	1.64 (0.20)	3.21 (0.07)	6.07 (0.01)	15.32 (0.00)	25.73 (0.00)	20.69 (0.00)	24.37 (0.00)	55.76 (0.00)
dh3			0.00 (0.96)	0.25 (0.62)	1.45 (0.23)	7.27 (0.01)	15.39 (0.00)	12.10 (0.00)	16.06 (0.00)	45.36 (0.00)
dh4				0.28 (0.60)	1.48 (0.22)	7.10 (0.01)	14.91 (0.00)	11.83 (0.00)	15.79 (0.00)	44.69 (0.00)
dh5					0.47 (0.49)	4.48 (0.03)	10.97 (0.00)	8.70 (0.00)	12.60 (0.00)	40.21 (0.00)
dh6						1.97 (0.16)	6.75 (0.01)	5.32 (0.02)	8.95 (0.00)	34.61 (0.00)
dh7							1.54 (0.21)	1.15 (0.28)	3.73 (0.05)	25.29 (0.00)
dh8								0.00 (0.96)	0.91 (0.33)	17.84 (0.00)
dh9									0.87 (0.35)	16.58 (0.00)
dh10										9.36 (0.00)

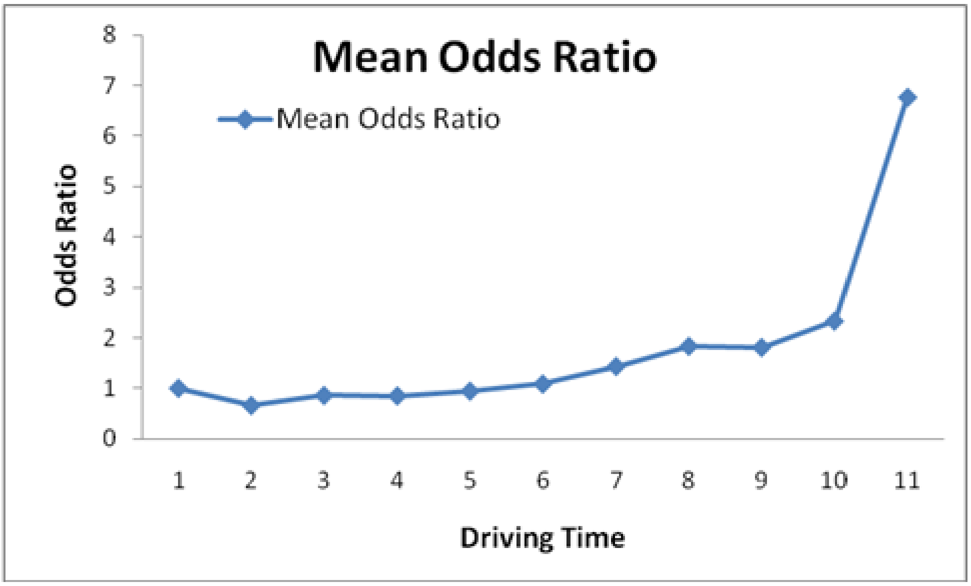


Figure 30. Aggregate Odds Ratio as Function of Hours Driving

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5. SUMMARY AND CONCLUSIONS

This study performed both qualitative and quantitative analyses of commercial motor vehicle driver hours of service to assess the implications of particular policies on the odds of a crash. The outcomes studied were crashes reported by the trucking companies cooperating with the study. These crashes involved either a fatality, an injury requiring medical treatment away from the scene of the crash, or a towaway. Carrier-supplied driver logs for periods of 1–2 weeks prior to each crash were used and compared to a random sample (two drivers) of non-crash-involved drivers selected from the same company, terminal, and month using a case-control logistic regression formulation. Data from 2004–05 and 2010 were collected from a total of 1,564 drivers. This is the methodology identified in the proposal and has been used by the team in many previous research studies (Jovanis et al., 1991; Kaneko and Jovanis, 1992; Lin et al., 1993; Lin et al., 1994).

Data were separated into TL and LTL analyses because previous research indicated substantive differences in crash contributing factors for these two segments of the trucking industry. In total, 878 drivers (318 crash-involved and 560 controls) were analyzed in TL operations and 686 drivers (224 crash-involved and 462 controls) were analyzed in LTL operations.

Statistical tests were performed to determine whether it is appropriate to combine the data from 2004–05 and 2010. The study team was concerned that there might be differences in the factors contributing to crashes since 5–6 years elapsed between the data collection periods. A series of Chow tests (Greene, 2003) were performed comparing the two datasets. These tests indicate that there is limited evidence to support the position that the two sets of data are drawn from datasets with different underlying crash associations. The study team reached this conclusion because only the first Chow test, the one with driving time only as a predictor, rejects the null hypothesis. When additional predictors are added, there is 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 datasets across 2004–05 and 2010.

The study 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 to a baseline condition) and the presence of a range of driving-related predictors, including cumulative hours driving, driving patterns over multiple days, time of day, breaks during driving, and the 34-hour recovery policy.

Findings of the research include:

- Driving time was associated with increased crash odds in the LTL analysis. Analysis of LTL data shows a strong and consistent pattern of increase in crash odds as driving time increases. The highest odds are in the 11th hour. There is a consistent increase after the 5th hour through the 11th hour. Specifically: the increase in odds is statistically significant in the 6th hour. The crash odds are significantly higher here than all previous hours except the 5th. The 7th hour is significantly higher than first 5, but not the 6th; the 8th hour is significantly higher than hours 1–6 and barely higher than the 7th hour; the 9th hour is higher than hours 1–7 and barely higher than the 8th hour; the 10th hour is higher than hours 1–8 and not higher than hour 9; and the 11th hour is higher than all previous hours. Use of interaction terms in the TL models revealed associations between some multiday driving patterns and increased crash risk with driving times in the 7–11 hour range. TL drivers who drive during the day have increased odds of a crash with long driving hours. These driving patterns result in their extended hours occurring in late afternoon and early evening when higher traffic levels are possible.

- Several analyses were conducted concerning breaks from the driving task. The study team considered a driving break as any time during a driving period when a driver went from driving status to either in a sleeper berth or off duty. When these events occurred during a trip, the odds of a crash were reduced for both TL and LTL drivers (by 32 percent and 51 percent respectively for two breaks).
- Studies were also conducted of the 34-hour recovery period. This is defined as a period of time consecutively off duty, or off duty in combination with sleeper berth use, in which at least 34 hours elapses. As used in this report, it does not imply that cumulative driving hours were restarted to zero thereafter. 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 to 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-hour recovery were for a trip starting immediately after a period of at least 34 hours off duty compared to a baseline trip (starting at night or day) without the 34-hours off duty. All tests of the 34-hour recovery showed an increase in crash odds (significant or barely significant) for both TL and LTL drivers compared to a baseline of starting a trip without the 34 hours off duty. The increased crash odds in the quantitative models were corroborated by comparison of driving patterns and relative risk for both the TL and LTL analyses. Multiday driving patterns with the higher crash relative risk consistently, but not exclusively, involved drivers returning from extended periods off duty.
  - More detailed models were constructed to compare the joint effects of the 34-hour recovery and driving at night or during the day. Starting a trip during the day without a restart had the lowest odds of a crash. Starting a trip at night with a 34-hour recovery resulted in a 58–64-percent increase in crash odds compared to a daytime trip without the recovery. LTL drivers experienced a 150-percent increase in the odds of a crash when using a 34-hour recovery and returning to work during the day compared to the no-recovery daytime return to work.
- Targeted analyses of the 34-hour restart policy using a subset of the data from 2010 showed that the occurrence of a “pseudo-violation” over 2 days is associated with an increase in the odds of a crash. Here “pseudo-violation” is defined as hours driving and working that would have violated the 70-hours-in-8-days rule, had the 34-hour restart not been in effect. This increase in crash odds was not apparent when the extended work allowed by the restart occurred over 1 day only. In fact, there was some evidence of a reduction in crash odds in this situation. Care is needed in interpreting this finding too broadly as the analysis included crash-involved drivers only for one carrier over a limited time period. The case-control application used in the restart analysis does not have the record of success of the method applied more generally in Section 4. More testing is recommended.

APPENDIX A: ADDITIONAL DATA ANALYSES

ANALYSES UNDERLYING COMBINING 2004–05 DATA WITH DATA FROM 2010

Table 29 summarizes the results of a series of statistical tests comparing the data from the 2004–05 dataset to those from 2010. These are a series of Chow tests (Greene, 2003) comparing the two datasets. The objective of the tests was to determine the efficacy of combining the 2004–05 and 2010 data together. The study team was concerned that there might be differences in the factors contributing to crashes in the two datasets since 5–6 years elapsed between the data collection periods. The team used the Chow test to explore the utility of combining the two datasets.

The Chow test compares the log-likelihood of a pooled model (the model with 2004–05 data combined with 2010 data) with the log-likelihoods obtained by splitting the data using some criterion (in this case, the years when the data were collected). In most cases, researchers use this technique to test for segmentation in the data; (i.e., structural differences in segments of the data that would result in different associations between predictors and the dependent variable; in this case, crash occurrence and driver hours).

Four model formulations were tested (Specifications 1–4 in Table 29) paralleling the structure of the modeling conducted in the study. Specification 1 used driving time only; Specification 2 used driving time and driving breaks; Specification 3 used the previous 2 and added a night variable representing whether the trip of interest occurred at night. Finally, Specification 4 enhanced Specification 3 by adding an indicator variable, which is a 1 if there was a 34-hour recovery period (or longer) immediately prior to the day of interest. Rejection of the null hypothesis means there is evidence that the segmented models are different and predict better than a pooled model.

Specification 1 (with driving hours only) indicated a significant improvement of model fit with segmentation at the level of $p = 0.10$. However, all subsequent tests (Specifications 2–4 in Table 29) with additional predictors failed to reject the null hypothesis. These tests indicated that there is limited evidence to support the position that the two sets of data are drawn from datasets with different underlying crash associations. The study team reached this conclusion because only the first Chow test, the one with driving time only as a predictor, rejects the null hypothesis. When additional predictors are added, including many that are similar to those used during the modeling, there is 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 datasets across 2004–05 and 2010.

Table 29. Models Used in Chow Test for Combining 2004–05 Data with 2010

	Specification 1			Specification 2			Specification 3			Specification 4		
VARIABLES	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**
dh2	-0.489	-0.624	-0.283	-0.468	-0.605	-0.270	-0.465	-0.601	-0.269	-0.468	-0.602	-0.269
(Standard Error)	(0.186)	(0.243)	(0.292)	(0.186)	(0.243)	(0.293)	(0.186)	(0.243)	(0.293)	(0.186)	(0.243)	(0.293)
P-value	0.009	0.010	0.333	0.012	0.013	0.356	0.012	0.014	0.358	0.012	0.013	0.359
dh3	0.025	0.074	-0.050	0.055	0.098	-0.023	0.059	0.104	-0.021	0.056	0.102	-0.022
(Standard Error)	(0.165)	(0.204)	(0.279)	(0.165)	(0.204)	(0.279)	(0.165)	(0.204)	(0.279)	(0.165)	(0.204)	(0.280)
P-value	0.879	0.718	0.857	0.737	0.630	0.935	0.719	0.610	0.941	0.734	0.616	0.937
dh4	-0.014	0.104	-0.220	0.030	0.138	-0.179	0.035	0.146	-0.176	0.032	0.144	-0.178
(Standard Error)	(0.169)	(0.208)	(0.291)	(0.169)	(0.208)	(0.291)	(0.169)	(0.208)	(0.291)	(0.169)	(0.208)	(0.291)
P-value	0.935	0.617	0.449	0.861	0.506	0.538	0.837	0.483	0.544	0.851	0.488	0.542
dh5	-0.180	-0.281	-0.021	-0.124	-0.239	0.036	-0.118	-0.229	0.039	-0.119	-0.230	0.040
(Standard Error)	(0.182)	(0.238)	(0.286)	(0.182)	(0.238)	(0.286)	(0.182)	(0.238)	(0.285)	(0.182)	(0.238)	(0.286)
P-value	0.324	0.239	0.942	0.496	0.316	0.899	0.516	0.335	0.891	0.512	0.333	0.889
dh6	0.184	0.235	0.120	0.265	0.289	0.228	0.273	0.300	0.233	0.270	0.299	0.233
(Standard Error)	(0.171)	(0.214)	(0.286)	(0.171)	(0.214)	(0.285)	(0.171)	(0.214)	(0.284)	(0.171)	(0.214)	(0.285)
P-value	0.281	0.272	0.675	0.120	0.175	0.423	0.110	0.160	0.412	0.113	0.162	0.414
dh7	0.298	0.313	0.300	0.396	0.392	0.407	0.404	0.404	0.411	0.403	0.404	0.406
(Standard Error)	(0.174)	(0.221)	(0.284)	(0.174)	(0.220)	(0.283)	(0.173)	(0.220)	(0.282)	(0.173)	(0.220)	(0.283)
P-value	0.086	0.156	0.290	0.022	0.076	0.150	0.020	0.066	0.146	0.020	0.067	0.151
dh8	0.477	0.447	0.547	0.587	0.539	0.655	0.595	0.552	0.660	0.595	0.552	0.661
(Standard Error)	(0.179)	(0.231)	(0.285)	(0.179)	(0.232)	(0.285)	(0.179)	(0.231)	(0.285)	(0.179)	(0.231)	(0.285)
P-value	0.008	0.054	0.055	0.001	0.020	0.021	0.001	0.017	0.020	0.001	0.017	0.020
dh9	0.508	0.677	0.263	0.636	0.786	0.386	0.642	0.797	0.390	0.642	0.796	0.394
(Standard Error)	(0.200)	(0.246)	(0.343)	(0.200)	(0.247)	(0.345)	(0.200)	(0.247)	(0.344)	(0.200)	(0.247)	(0.344)
P-value	0.011	0.006	0.445	0.002	0.001	0.263	0.001	0.001	0.258	0.001	0.001	0.252

	Specification 1			Specification 2			Specification 3			Specification 4		
VARIABLES	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**
dh10	0.629	0.884	0.169	0.783	1.022	0.308	0.786	1.032	0.302	0.789	1.031	0.330
(Standard Error)	(0.246)	(0.294)	(0.461)	(0.247)	(0.296)	(0.465)	(0.248)	(0.296)	(0.465)	(0.248)	(0.296)	(0.466)
P-value	0.011	0.003	0.714	0.002	0.001	0.507	0.002	0.001	0.516	0.001	0.001	0.479
dh11	1.508	1.681	1.239	1.769	1.875	1.538	1.762	1.867	1.528	1.748	1.861	1.516
(Standard Error)	(0.301)	(0.371)	(0.521)	(0.311)	(0.382)	(0.546)	(0.312)	(0.384)	(0.548)	(0.312)	(0.383)	(0.554)
P-value	0.000	0.000	0.017	0.000	0.000	0.005	0.000	0.000	0.005	0.000	0.000	0.006
numbreak12_1				-0.612	-0.446	-0.713	-0.618	-0.439	-0.727	-0.613	-0.436	-0.734
(Standard Error)				(0.111)	(0.159)	(0.162)	(0.112)	(0.160)	(0.163)	(0.112)	(0.160)	(0.163)
P-value				0.000	0.005	0.000	0.000	0.006	0.000	0.000	0.007	0.000
numbreak12_2				-1.099	-0.832	-1.400	-1.100	-0.830	-1.401	-1.093	-0.823	-1.424
(Standard Error)				(0.172)	(0.224)	(0.277)	(0.173)	(0.225)	(0.277)	(0.172)	(0.225)	(0.272)
P-value				0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
numbreak12_3				-0.363	-0.464	-0.271	-0.365	-0.468	-0.270	-0.358	-0.465	-0.255
(Standard Error)				(0.0685)	(0.108)	(0.0898)	(0.0685)	(0.108)	(0.0897)	(0.0683)	(0.108)	(0.0893)
P-value				0.000	0.000	0.003	0.000	0.000	0.003	0.000	0.000	0.004
night							-0.112	-0.126	-0.141	-0.113	-0.124	-0.164
(Standard Error)							(0.0876)	(0.111)	(0.145)	(0.0875)	(0.111)	(0.146)
P-value							0.201	0.259	0.331	0.198	0.265	0.259
h34_0										0.222	0.077	0.485
(Standard Error)										(0.107)	(0.137)	(0.174)
P-value										0.038	0.575	0.005

	Specification 1			Specification 2			Specification 3			Specification 4		
VARIABLES	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**	**Pooled**	**2010**	**2004–05**
Constant	-2.969	-2.894	-3.096	-2.747	-2.753	-2.743	-2.690	-2.689	-2.673	-2.729	-2.703	-2.747
(Standard Error)	(0.112)	(0.140)	(0.189)	(0.116)	(0.143)	(0.201)	(0.127)	(0.157)	(0.217)	(0.129)	(0.160)	(0.218)
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	10,922	6,285	4,637	10,922	6,285	4,637	10,922	6,285	4,637	10,922	6,285	4,637
Pseudo R^2	0.0141	0.0204	0.00916	0.0331	0.0350	0.0339	0.0335	0.0354	0.0345	0.0343	0.0355	0.0386
Log likelihood	-2232	-1367	-856.3	-2189	-1347	-834.9	-2188	-1346	-834.4	-2186	-1346	-830.9
Chow Test P-value	0.105			0.409			0.439			0.292		
Chow Test Conclusion	Barely reject			Accept			Accept			Accept		

Table 30. Crash Odds as Function of Driving Time, Driving Pattern, Interactions, and Driving Breaks—LTL

Coefficients	Estimate	Standard Error	z value	Pr(>|z|)	Odds Ratio	Lower 95% CI for OR	Upper 95% CI for OR
(Intercept)	-2.943	0.295	-9.964	< 2e-16	0.053	0.030	0.094
dh2	-0.793	0.426	-1.861	0.063	0.453	0.196	1.043
dh3	0.008	0.339	0.023	0.982	1.008	0.518	1.960
dh4	-0.258	0.374	-0.690	0.490	0.772	0.371	1.608
dh5	0.540	0.317	1.703	0.089	1.716	0.922	3.196
dh6	0.550	0.350	1.573	0.116	1.734	0.873	3.443
dh7	0.912	0.324	2.818	0.005	2.489	1.320	4.695
dh8	1.476	0.301	4.897	0.000	4.374	2.423	7.895
dh9	1.830	0.311	5.883	0.000	6.233	3.388	11.467
dh10	1.924	0.377	5.107	0.000	6.849	3.273	14.332
dh11	3.526	0.507	6.953	0.000	33.999	12.582	91.870
Pattern 1	-1.131	0.308	-3.671	0.000	0.323	0.176	0.590
Pattern 2	-1.040	0.346	-3.009	0.003	0.353	0.179	0.696
Pattern 3	-0.515	0.332	-1.553	0.121	0.597	0.312	1.145
Pattern 5	-0.099	0.281	-0.350	0.726	0.906	0.522	1.573
Pattern 6	-0.733	0.298	-2.457	0.014	0.480	0.268	0.862
Pattern 7	-0.336	0.269	-1.246	0.213	0.715	0.422	1.212
Pattern 8	-0.479	0.306	-1.568	0.117	0.619	0.340	1.127
Pattern 9	-0.851	0.386	-2.208	0.027	0.427	0.201	0.909
Pattern 10	-1.235	0.375	-3.295	0.001	0.291	0.140	0.606
numbreak12_1	-0.141	0.161	-0.872	0.383	0.869	0.633	1.192
numbreak12_2	-0.657	0.277	-2.373	0.018	0.518	0.301	0.892
numbreak12_3	-0.071	0.110	-0.648	0.517	0.931	0.750	1.156
dh7:pattern 2	1.352	0.575	2.352	0.019	3.867	1.253	11.934
dh10:pattern 4	1.594	0.770	2.070	0.038	4.922	1.089	22.257
dh6:pattern 7	1.095	0.488	2.241	0.025	2.988	1.147	7.784
dh2:pattern 9	2.318	0.780	2.971	0.003	10.158	2.201	46.879

AIC = 1,650.5

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GLOSSARY

Akaike Information Criterion—a goodness-of-fit measure for statistical models that includes consideration of the log likelihood and the number of parameters estimated.

Confidence interval—a statistical measure of the uncertainty associated with a parameter estimate.

Electronic onboard recorder (EOBR)—an electronic device installed in a commercial motor vehicle and used to record the amount of time a vehicle is driven.

Hours of service—the collection of policies implemented by FMCSA to regulate the hours of work and driving by motor carrier drivers.

Odds ratio—the ratio of the odds of a crash for particular value of a predictor compared to a baseline value for the predictor. An example is the odds ratio for driving 8 hours, which would be expressed compared to the odds of a crash in the first hour of driving.

Less than truckload—a type of trucking operation that primarily moves freight between company-owned terminals. More than one shipper has goods on the truck. Before and after the movement between company terminals, goods are picked up and delivered by different drivers and vehicles and a designated location for the goods being moved. This study only considers the movement between company-owned terminals.

Relative risk—a comparison of crash risk for two categories of variables. In this study the comparison is between crash risk with one multiday driving pattern (computed as the number of crashes divided by the total number with the pattern) compared to a baseline patterns which has the highest percentage of crashes with a common driving pattern.

Truckload—a trucking service that typically moves freight from one firm with a pick-up, movement and delivery from loading dock to loading dock with one vehicle. Only one firm's goods are on the truck. Drivers providing this type of service typically have more variable patterns of driving because of the origin to destination service provided.

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