UMTRI-2000-11

Hours of Service Regulatory Evaluation Analytical Support

Task 1: Baseline Risk Estimates and Carrier Experience

Final Report

Task 6
Engineering, Analytic and Research Support for Motor Carrier Safety Activities
Contract No. DTFH61-96-C-00038

submitted to
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Federal Highway Administration

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prepared by

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Notice

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16. Abstract

The objective of this project is to provide baseline information to assess the safety and economic impact of the proposed hours of service (HOS) options. The analysis is organized around driver/operation groups developed by Federal Motor Carrier Safety Administration (FMCSA) for the hours of service (HOS) options. This report provides preliminary information for a Notice of Proposed Rulemaking. Baseline estimates of the prevalence and risk of fatigue accidents are presented. Estimates of the number of vehicles, vehicle miles of travel and fatigue accidents are developed for populations affected by hours of service regulations. The incidence of fatigue accidents is combined with the population data to estimate the overall risk of fatigue accidents. These risk estimates are the necessary starting point for subsequent estimates of the safety impact of each HOS option.

A preliminary assessment of the impact on drivers and motor carriers is also presented, including baseline information on driver wages, hours and working conditions. This information shows that drivers do not comply with current regulations. Estimates are presented of the cost of compliance with the current law, as well as social opportunity cost of the proposed policy changes. Qualitative estimates of the industry impact on daily and weekly schedule and daily and weekly maximum hours are presented.

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SI* (MODERN METRIC) CONVERSION FACTORS

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		
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
NOTE: Volumes greater than 1000 L shall be shown in 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 (exact)		
°F	Fahrenheit temperature	5(F-32)/9 or (F-32)/1.8	Celcius temperature	°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

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	35.71	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 (exact)		
°C	Celcius temperature	1.8C + 32	Fahrenheit temperature	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-lamberts	fl
		FORCE and 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 September 1993)

Acknowledgement

Sections 1.1 and 1.2 were written primarily by Dr. Kenneth L. Campbell, with assistance from Dr. Daniel Blower. Dr. Blower conducted the analysis of the 1992 Truck Inventory and Use Survey data and the 1997 Texas accident data, and prepared the Trucks Involved in Fatal Accidents (TIFA) files from 1981–1996 for analysis. The analysis of the TIFA data and rate calculations were carried out by Dr. Campbell.

Sections 1.1 and 1.2 rely heavily on the Trucks Involved in Fatal Accidents Survey that has been conducted by the Center for National Truck Statistics at UMTRI since 1981. The TIFA data are a supplement to the Fatality Analysis Reporting System (FARS) provided by the National Highway Traffic Safety Administration.

Section1.3 was produced by a team of economists associated with the University of Michigan Institute of Labor and Industrial Relations (ILIR). Data manipulation for this report based on the UMTIP Driver Survey was provided by Dr. Monaco. Dr. Belzer did the final writing, along with integrative work. Some sections, as originally provided by contributors, were modified in significant respects by Dr. Belzer, so he is responsible for errors. Research assistance was provided by Michael Dover of ILIR

Section 1.3.2 was written in two sections. The first section was produced by Dr. Donald Grimes and Dr. George Fulton of the University of Michigan ILIR. This analysis uses several sources, including the Current Population Survey (CPS), the UMTIP Driver Survey, the Truck Inventory and Use Survey (TIUS), and Form M of interstate motor carrier operations, currently collected by the US DOT Bureau of Transportation Statistics. Help in estimating the number of owner operators was received from the Owner Operator Independent Driver Association (OOIDA). The second section of 1.3.2 was written primarily by Dr. Stephen Burks of ILIR. Dr. Burks received data analysis assistance and modeling collaboration from Dr. Monaco, as well as econometric assistance and advice from Dr. Daniel Lass and Dr. Dale Ballou of the University of Massachusetts.

Section 1.3.3 was written by Dr. Belzer.

The analyses presented in Section 1.3 are largely based on data collected by the University of Michigan Trucking Industry Program (UMTIP) Driver Survey. These data were collected by Dr. Dale Belman of the University of Wisconsin - Milwaukee and Dr. Kristin Monaco of the University of Wisconsin - Eau Claire, with funding and support from UMTIP..

Finally, the material in Section 1.3 provided by Dr. Belzer was integrated with the first two sections by Dr. Campbell.

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Phase 1: Baseline Risk Estimates and Carrier Experience

Introduction

The objective of this project is to provide baseline information to assess the impact of the proposed hours of service (HOS) options, including safety and economic impacts. The analysis is organized around driver/operation groups developed by Federal Motor Carrier Safety Administration (FMCSA) for the hours of service (HOS) options. The objective of Phase 1 is to provide preliminary information for a Notice of Proposed Rulemaking.

One objective of this work is to develop baseline estimates of the risk of fatigue accidents by the driver/operation subsets identified in the HOS options under consideration. Baseline estimates of the number of vehicles, vehicle miles of travel and fatigue accidents will be refined to characterize the populations affected by hours of service regulations. The FHWA Office of Motor Carriers (now FMCSA) prepared preliminary assessments of the crash problem size and driver population. The primary objective of this work is to separate the estimates of fatigue accidents by the driver/operation subsets identified in the HOS options under consideration. The accident data will be developed in Section 1.1. The incidence of fatigue accidents will be combined with the population data, developed in Section 1.2, to estimate the overall risk of fatigue accidents for each driver/operation option. These risk estimates are the necessary starting point for subsequent estimates of the safety impact of each HOS option.

The impact on drivers and motor carriers is addressed in Section 1.3. This Section is divided into three activities. Section 1.3.1 will provide baseline information on driver schedules from the University of Michigan Trucking Industry Program (UMTIP) driver survey. A preliminary assessment of the driver impact is addressed in Section 1.3.2, while the industry impact is addressed in Section 1.3.3

1.1: Accident Data

The Federal Motor Carrier Safety Administration (FMCSA) prepared a brief "Accident Problem Size Assessment: Large Truck Accidents Related Primarily to Fatigue" in September 1998. This task adopts the same definition of fatigue as coded on police accident reports (and in FARS). The objective of this task is to expand on the FMCSA analysis by distinguishing driver/operation subsets identified in the HOS options. This will be accomplished by using the UMTRI Trucks Involved in Fatal Accidents (TIFA) data that supplements the FARS (Fatality Analysis Reporting System) data. The TIFA file offers several advantages for this analysis. In addition to the FARS variables, TIFA has more complete and accurate truck type codes, area of operation (interstate, intrastate), carrier type (private, for-hire), and the trip type variable based on one-way intended trip distance (local delivery, 51-100 miles, 101-200 miles, 201-500 miles, over 500 miles) used in the 1992 Truck Inventory and Use Survey (TIUS). These variables will be used to identify driver/operation subsets that correspond to those identified in the HOS options.

The levels for coding trip distance have changed over the period of the TIFA file. From 1980 to 1990, a two level coding (local, over the road) taken from the MCS 50-T form was used. From 1991 to 1993, three levels corresponding to the 1987 Truck Inventory and Use Survey (local, 50-200, and greater than 200 miles) were used in TIFA. Starting in 1994, the five level coding (local, 50-100, 100-200,200-500, >500) from the 1992 Truck Inventory and Use Survey was adopted in TIFA. Distances are the intended one-way trip distance. Consequently, the 5 level trip distance variable is only available in the 1994 to 1996 TIFA files. The three level trip distance is available in the 1991 to 1996 files by combining the five level classification. Additional variables in the preliminary analysis are time of day and hours driving at the time of the accident.

1.1.1 Coding of Fatigue in Fatal Accidents

The measures of interest, or dependent variables, for this analysis are prevalence and risk. Prevalence measures the size of the problem. Prevalence is most important because it identifies the target population. Risk is of secondary importance, but may provide insight to the role of explanatory factors. Risk estimates are also necessary to estimate potential benefits when the countermeasures may change the underlying exposure amount or distribution.

Prevalence is the annual frequency of, in this case, truck driver fatigue in fatal accidents (and non-fatal later). For the six years, 1991 to 1996, fatigue is coded as a contributing factor for 511 trucks drivers out of a total of 27,463 medium and heavy trucks involved in fatal accidents over the six year period. The 511 cases of truck driver fatigue coded correspond to an annual average of 85 per year, or 1.9 percent of all medium and heavy trucks involved in fatal accidents in the U.S.

Fatigue is shown by year in Figure 1. There is a clear downward trend over the 17 years shown. A quick review of the coding of fatigue by State shows some large variations. These results are based on a 6-year TIFA file, 1991-1996. The coding on fatigue is taken from the "driver related factors" variables in FARS. Up to 3 factors can be selected from a list of nearly 100 choices covering the broad categories of physical/mental condition, vision obscured, avoiding or swerving, and miscellaneous. "Drowsy, sleepy, asleep, fatigued" is the first factor listed (01). For this analysis, the truck driver is classified as fatigued if 01 is coded for any of the three contributing factors for the truck driver. For most cases, no driver related factor is coded. "None" is coded about 60 percent of the time for the first driver related factor, 80 percent for the second factor, and 95 percent for the third. When fatigue is coded, it is indicated as the first driver related factor in about 75 percent of the cases (and is coded as the second or third factor for the rest). FARS analysts must rely on the original police accident report. To the extent that the reporting of fatigue varies from state to state, it is probably a reflection of the availability of coding or information on the original police report. In general, the FARS data are very accurate and complete. Fatigue, of course, is particularly difficult to assess, even with in-depth investigations, since there is no physical evidence of fatigue. The assessment is usually based on statements of the involved parties or witnesses, or inferred from the sequence of events.

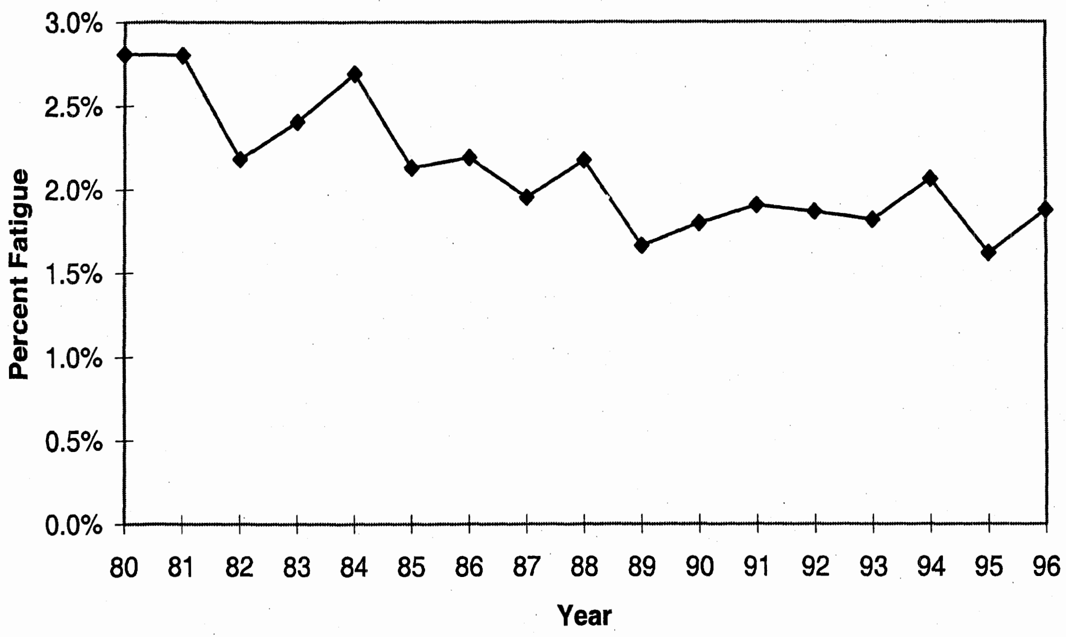

Figure 1: Fatigue by Year, TIFA 1980-1996

States have been sorted in order of increasing fatigue and are shown in Figure 2. Note several states with no fatigue reported in six years. The TIFA file is a sample of the FARS census file. Comparison of the TIFA data with the FARS census file for the years 1993 to 1995 show only minor differences. North Carolina and Wisconsin each report one fatigue case over that period, as compared to none in the TIFA file. Aggregate totals for the year differ by only a case or two. Since fatigue occurs primarily on rural roads, difference in urbanization from state to state may influence the state wide proportion of fatigue. The ranking of states in Figure 2 is repeated for rural accidents only in Figure 3.

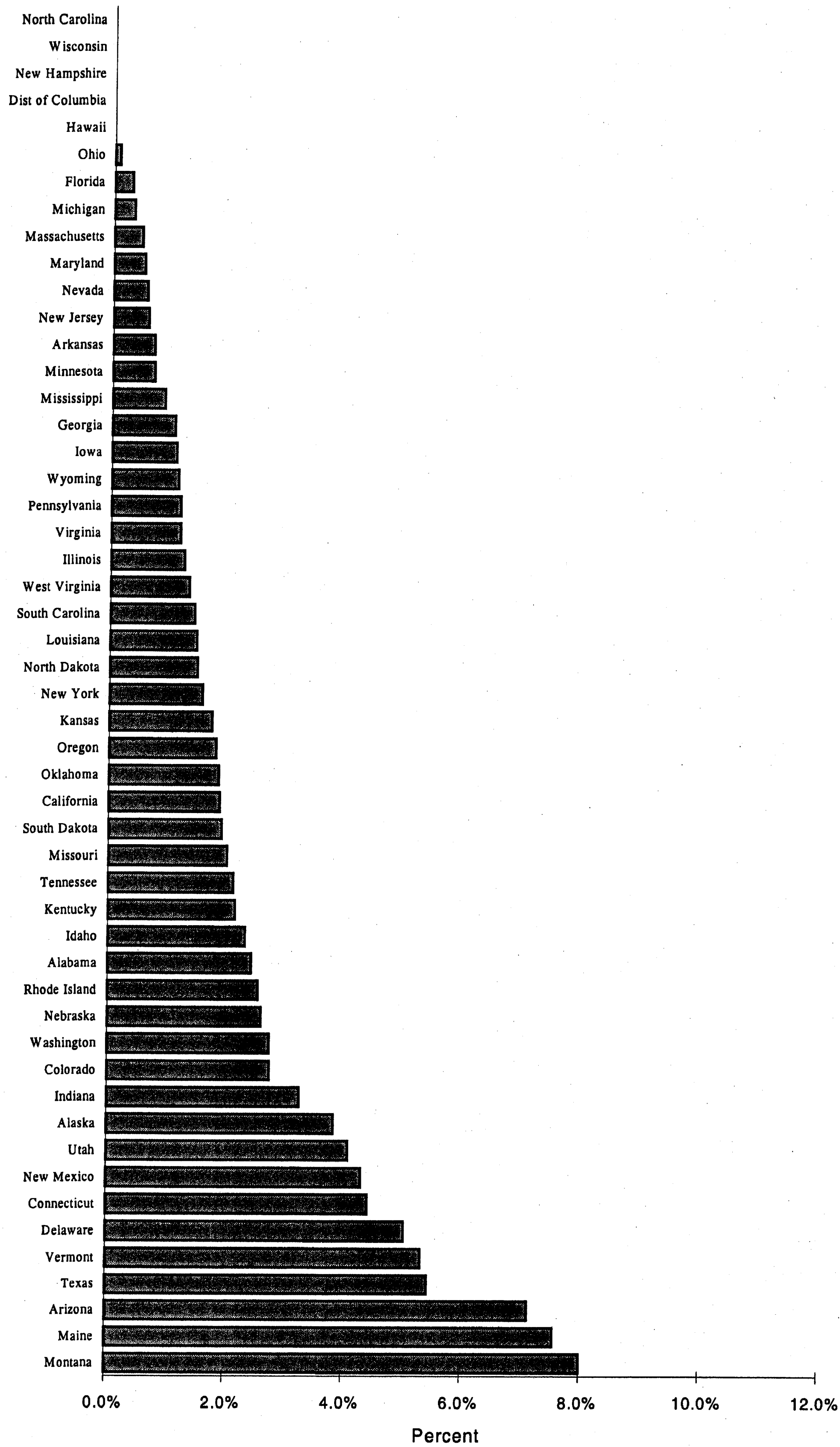

Figure 2: Fatigue by State, TIFA 1991-1996

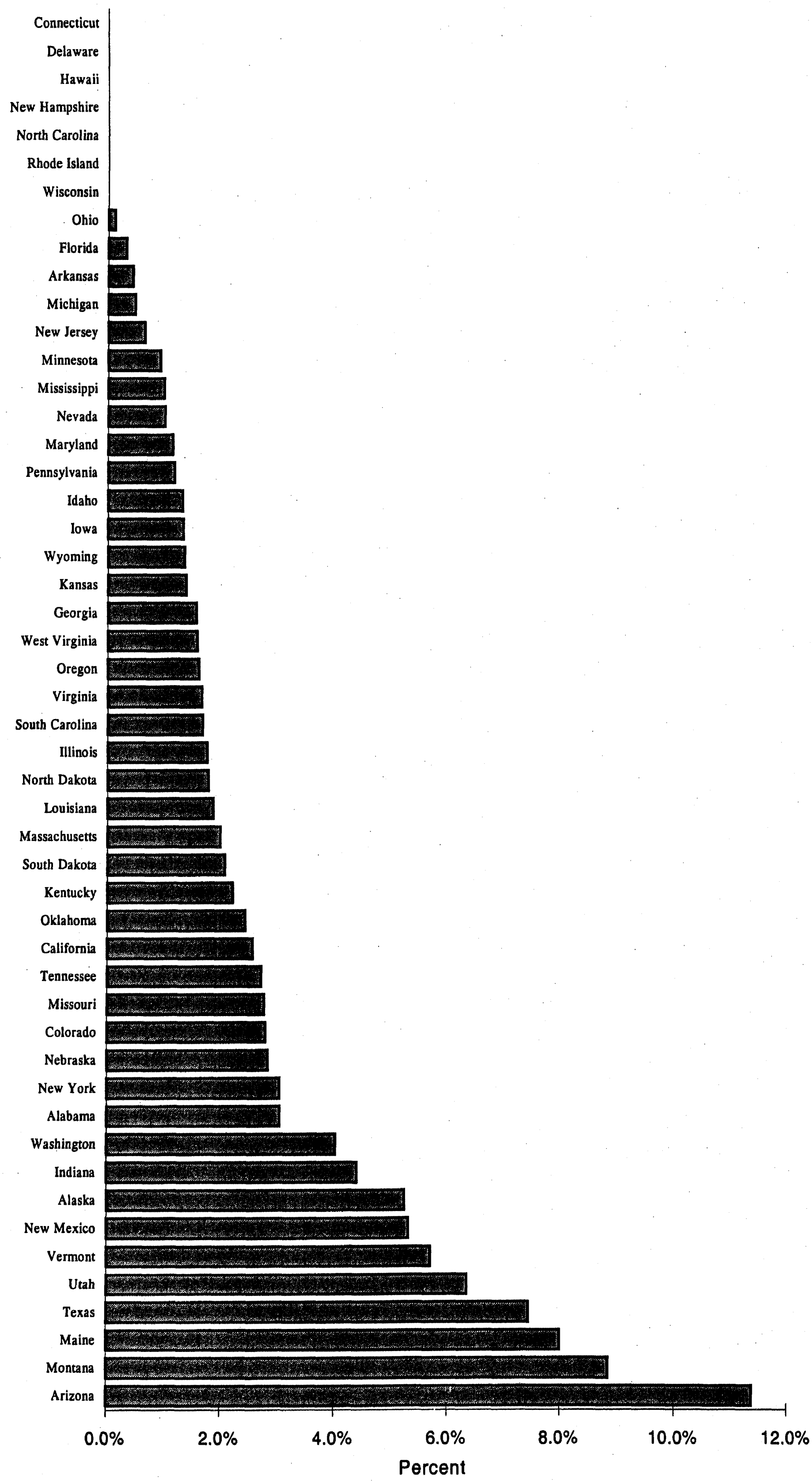

Figure 3: Fatigue by State for Rural Accidents Only, TIFA 1991-1996

A few changes are evident. Delaware and Connecticut drop to zero when only rural areas are included. Otherwise, the ordering of the two figures is similar. Of most concern, are 5 large states, shown in Table 1, with a total of only 9 fatigue cases in 6 years, or 0.2 percent of the truck drivers involved in fatal accidents in the 5 states (based on all accidents). This percentage is below the average (1.86 percent) by nearly a factor of 10. One might conclude that fatigue is underreported in these states. These states represent 20 percent of the national total, suggesting that the national average is also significantly underreported.

Table 1
States Reporting less than 0.5% Fatigue
TIFA 1991-1996

State	Fatigue	Total	Percent
Florida	5	1648	0.3%
Michigan	3	879	0.3%
North Carolina	0	1115	0.0%
Ohio	1	1167	0.1%
Wisconsin	0	573	0.0%
Total	9	5382	0.2%

A second group of states is shown in Table 2. This group also has a relatively low percentage of fatigue. However, this group includes some small states such as District of Columbia, Hawaii, and New Hampshire, and as a group represent only 10 percent of the national total. Consequently, they are of less concern.

Table 2
States Reporting 0.5% to 0.7% Fatigue
TIFA 1991-1996

State	Fatigue	Total	Percent
Arkansas	4	567	0.7%
Dist of Columbia	0	18	0.0%
Hawaii	0	25	0.0%
Maryland	2	377	0.5%
Massachusetts	1	208	0.5%
Minnesota	3	423	0.7%
Mississippi	5	559	0.9%
Nevada	1	173	0.6%
New Hampshire	0	61	0.0%
New Jersey	3	498	0.6%
Total	19	2909	0.7%

The remaining states, shown in Table 3, all report at least 1 percent fatigue among truck drivers involved in fatal accidents. As a group, these states account for 70 percent of the national total for fatal truck accidents. The average level of truck driver fatigue reported in these states is 2.5 percent, or about 35 percent higher than the overall figure for all states during the years 1991 to 1996.

Table 3
States Reporting more than 1% Fatigue
TIFA 1991-1996

State	Fatigue	Total	Percent
Alabama	21	860	2.4%
Alaska	1	26	3.8%
Arizona	31	435	7.1%
California	43	2280	1.9%
Colorado	9	326	2.8%
Connecticut	7	158	4.4%
Delaware	5	99	5.1%
Georgia	12	1118	1.1%
Idaho	4	171	2.3%
Illinois	12	962	1.2%
Indiana	28	857	3.3%
Iowa	5	454	1.1%
Kansas	6	343	1.7%
Kentucky	13	602	2.2%
Louisiana	8	541	1.5%
Maine	9	119	7.6%
Missouri	15	742	2.0%
Montana	10	125	8.0%
Nebraska	7	268	2.6%
New Mexico	12	278	4.3%
New York	16	1011	1.6%
North Dakota	1	67	1.5%
Oklahoma	9	481	1.9%
Oregon	7	384	1.8%
Pennsylvania	14	1190	1.2%
Rhode Island	1	39	2.6%
South Carolina	8	557	1.4%
South Dakota	2	104	1.9%
Tennessee	16	752	2.1%
Texas	117	2150	5.4%
Utah	7	171	4.1%
Vermont	4	75	5.3%
Virginia	8	677	1.2%
Washington	10	363	2.8%
West Virginia	4	299	1.3%
Wyoming	1	88	1.1%
Total	483	19172	2.5%

It may also be of interest to note the other extreme, states reporting the highest percentage of fatigue among truck drivers. Four states are substantially higher than the rest and these are listed separately in Table 4. Texas and Arizona share the boarder with Mexico, and Maine is the home of Parents Against Tired Truckers (PATT). Texas also has a very complete accident report that includes fatigue in a long list of "factor or conditions that may have contributed" to the collision that is printed on the report form.. The report states that this information is based on the officer's opinion. The Texas police-reported accident data may be a good source to look at fatigue in non-fatal collisions. Neither Arizona or Maine include fatigue as an explicit category on the accident report form.

Table 4
States Reporting the Most Fatigue
TIFA 1991-1996

State	Fatigue	Total	Percent
Arizona	31	435	7.1%
Maine	9	119	7.6%
Montana	10	125	8.0%
Texas	117	2150	5.4%
Total	167	2829	5.9%

As part of this look at fatigue by state, states were aggregated into four geographic regions. This result is shown in Table 5. As one may have expected, the percentage of fatigue among truck drivers is higher in the western states. However, this result is influenced by the state to state variations already discussed.

Table 5
Fatigue by Geographic Region
TIFA 1991-1996

State	Fatigue	Total	Percent
Northeast	131	9869	1.3%
Southeast	67	6609	1.0%
Northwest	50	2447	2.0%
Southwest	262	8487	3.1%
AL & HI	1	51	2.0%
Total	511	27463	1.9%

The reporting of fatigue was also examined for only collisions with one or more fatalities in the truck. This result is shown in Figure 4. Overall, 14 percent of all trucks involved in fatal accidents had one or more fatalities in the truck. Of the truck occupant fatalities, 9.5 percent (361 cases) were coded for truck driver fatigue. These fatigue cases are 70 percent of all fatigue coded for truck drivers in the TIFA data for 1991 to 1996. The proportion of fatigue in the non-truck fatalities is 0.6 percent. Again, the variation by state is substantial. The order of the states is essentially the same as Figure 2. The range of percentages is substantially higher, with several states reporting over 20 percent fatigue in truck driver fatalities and a few reporting 40 percent.

Figure 5 looks at the reporting of fatigue by state in the older TIFA files from 1980 to 1990. The ranking of states is very similar. Whatever the reasons for state to state differences, they seem to be fairly stable over the entire 17 years. The overall percentage of fatigue is somewhat higher in the 1980s, as shown by the yearly trend in Figure 1.

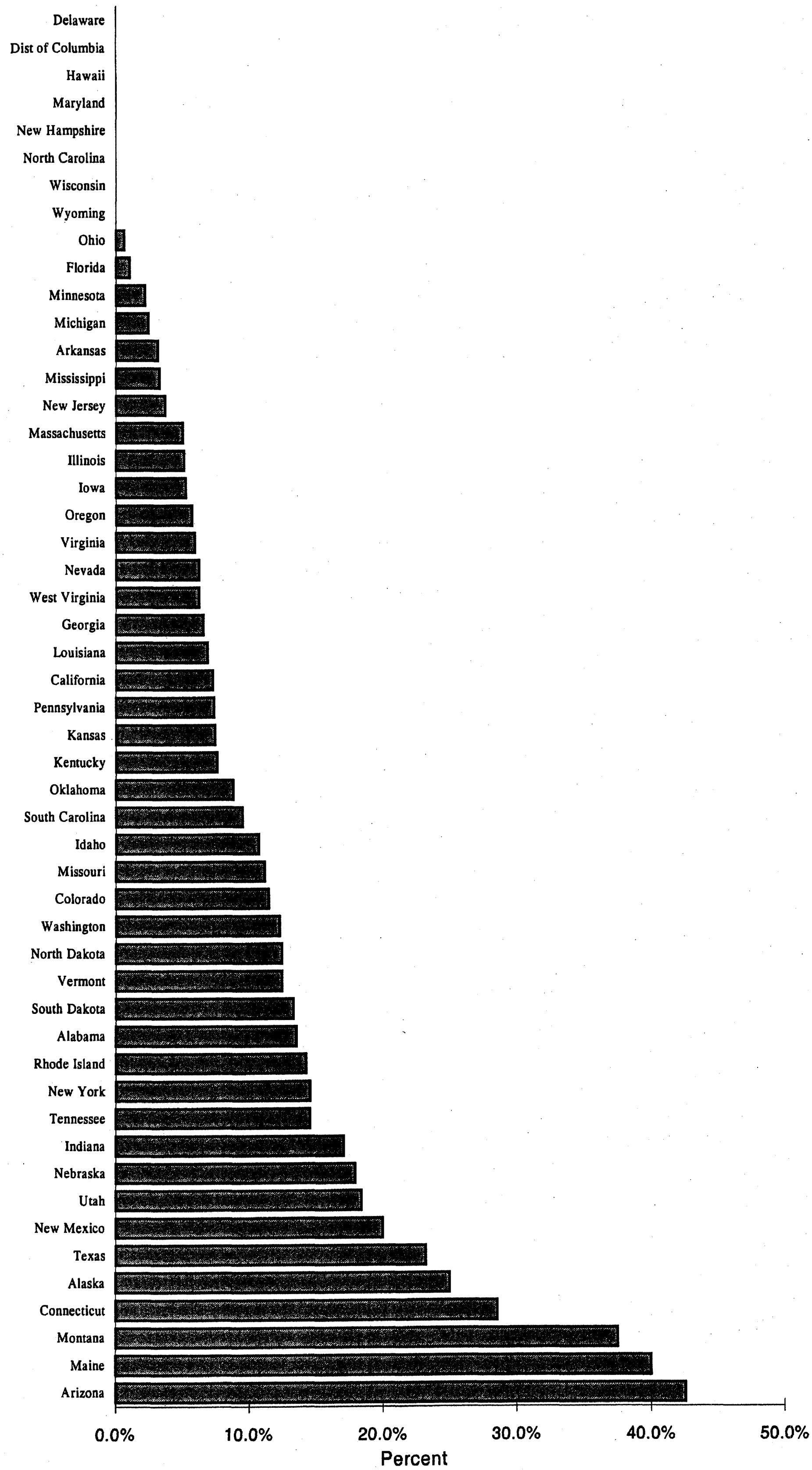

Figure 4: Fatigue by State for Truck Driver Fatalities, TIFA 1991-1996

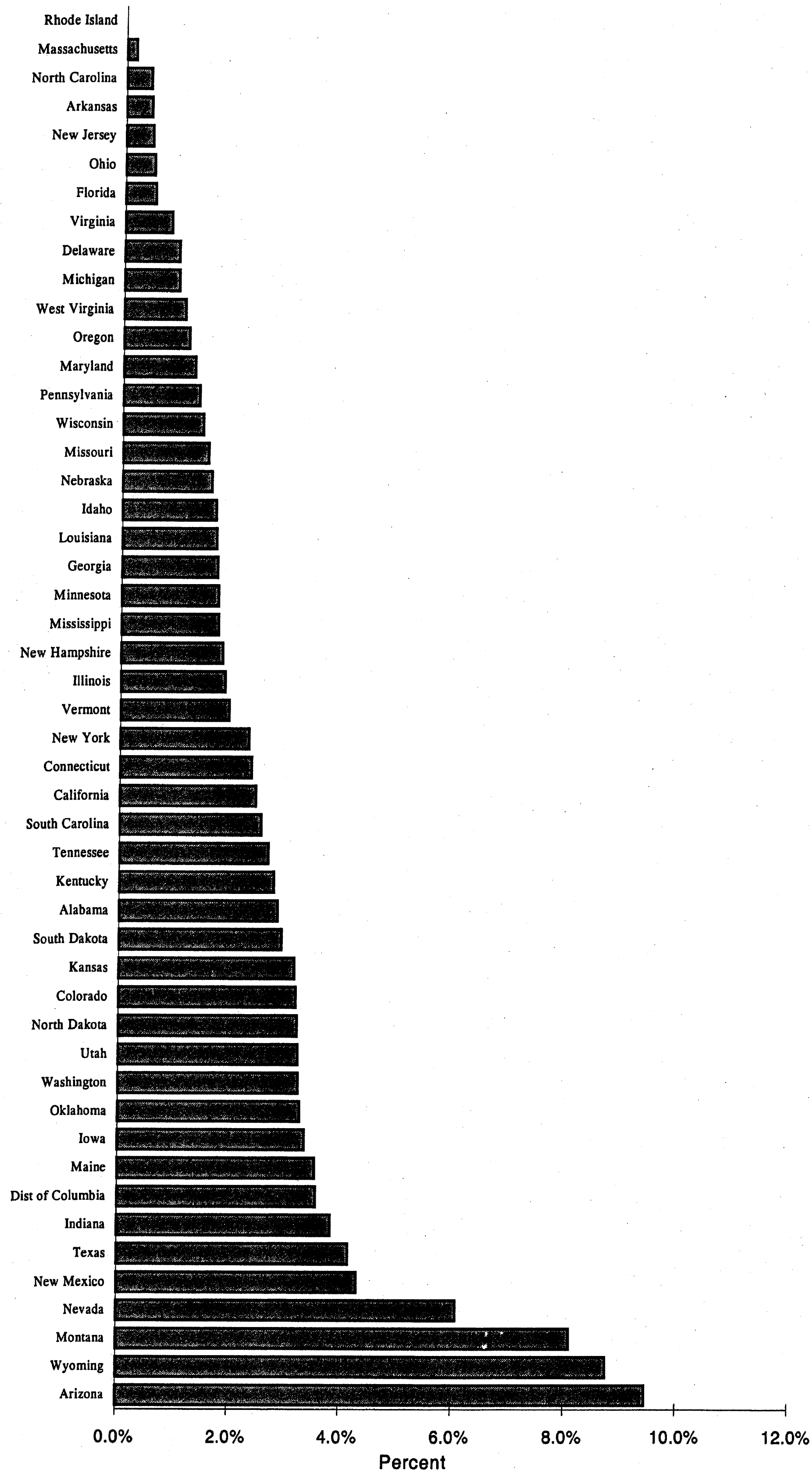

Figure 5: Fatigue by State, TIFA 1980-1990

The variations in fatigue reporting provide some insight to the difficulty of identifying the role of fatigue in accidents and the difficulty in determining the total incidence of fatigue nationwide. It seems clear that the overall proportion in fatal accidents, 1.86 percent from FARS/TIFA, underestimates the true value. The largest proportions of fatigue for individual states in the FARS file approach the levels observed from in-depth investigations. For example, values of 20 to 40 percent for truck occupant fatalities are in the same range reported by NTSB in their truck driver fatality study. Similarly, the range of truck driver fatigue in all medium and heavy truck fatal involvements among states (Figure 2) exceeds the range estimated from more in-depth examinations reported in the FMCSA Accident Problem Size Assessment for truck driver fatigue.

The remaining issue is to determine whether the variation in fatigue reporting from state to state should alter the planned safety analysis described here. One might consider limiting the states used to a subset with "better" reporting. But this creates the need to extrapolate back to national estimates, and introduces the problem as to whether the subset is still representative of the whole. As far as we know, the other variables in the analysis are not subject to the same kind of state to state variation. Consequently, the current approach will be to continue with the complete file. The information on state to state variations in the reporting of fatigue illustrates the uncertainty in our overall population estimate. This issue can be addressed by simply factoring up the observed proportions by whatever amount is felt to be most appropriate, as in the FMCSA analysis.

1.1.2 Prevalence of Fatigue in Fatal Accidents

The objective of this analysis of the prevalence of fatigue is to identify subsets that account for the greatest proportion of the fatigue cases. Consequently, all prevalence results will be presented as a percentage of the total for each table or figure. The sum of all bars on every figure is 100 percent. This holds when another variable is used to divide the data, such as straight trucks versus tractors. Overall percentages are shown so that the sum of all the straight truck bars plus the tractors is 100 percent. This approach maintains the relative proportions for each category (independent) variable.

Figures in this section are presented in pairs, two on a page. The top figure shows the distribution (prevalence) of all medium and heavy trucks involved in fatal accidents and the bottom figure is the distribution of all medium and heavy trucks involved in fatal accidents where truck driver fatigue was coded as a contributing factor. The top figure is shown only for reference, or perspective, to illustrate the overall pattern of fatal accidents involving medium and heavy trucks. For many factors, the distribution of all trucks involved in fatal accident reflects the underlying exposure. The overall fatal accident involvement can be thought of as the product of the exposure amount multiplied by the risk of involvement in a fatal accident per unit exposure. It will be shown in Section 1.2 using exposure estimates from TIUS, that the variations in risk were often less than the variation in exposure, so that the underlying exposure pattern is visible in the accident experience. Of course, this is not always the case and for variables without exposure data, one cannot know for sure.

The basic approach is illustrated in the following tables. The coding of truck driver fatigue is shown by the 5 trip distance categories in Table 6. The greatest portion, 36.6 percent, of the fatigue cases are in the trip distance greater than 500 miles category. The prevalence of truck driver fatigue will be examined in relation to many variables in order to better characterize the factors associated with the greatest proportion of truck driver fatigue.

Table 6
Truck Driver Fatigue, TIFA 1994-1996

	Trip Distance						
	Local	50-100	100-200	200-500	>500	Unknown	Total
Frequency	21	32	28	62	98	27	268
Percent	7.8%	11.9%	10.4%	23.1%	36.6%	10.1%	100.0%

It is also of interest to compare the distribution of the fatigue cases with the distribution of all cases, shown in Table 7. For the current example, the question is whether fatigue is over-represented in any of the trip distance categories. A finding that fatigue is over- or under-represented in specific trip distance categories indicates an association between the factor level and fatigue. Comparing these two tables, one sees that 36.6 percent of the fatigue cases are coded >500 miles trip distance whereas 15.5 percent of *all* trucks involved in fatal accidents are coded trip distance >500 miles. Thus, fatigue is over-represented in trips >500 miles by a factor of 2.35, the ratio of these two percentages, as shown in Table 8.

Table 7
All Trucks Involved in Fatal Accidents, TIFA 1994-1996

	Trip Distance						
	Local	50-100	100-200	200-500	>500	Unknown	Total
Frequency	5,685	1,655	1,462	2,041	2,244	1,346	14,433
Percent	39.4%	11.5%	10.1%	14.1%	15.5%	9.3%	100.0%

This calculation is convenient to use because it is scaled to always produce an overall figure of 1.0 for the aggregate. It is equivalent to the ratio of the percentage of cases coded fatigue in an individual category (98/2,244 = 4.4% for trips >500 miles) to the overall percent fatigue (268/14,433 = 1.9%). The ratio of 4.4 to 1.9 is 2.35. These percentages estimate the probability of fatigue given the truck is involved in a fatal accident. The ratio takes the form of a relative risk where the denominator is based on fatal accident involvement.

Table 8
Relative Risk of Fatigue based on Fatal Accident Involvement. TIFA 1994-1996

	Trip Distance						
	Local	50-100	100-200	200-500	>500	Unknown	Total
Relative Risk	0.20	1.04	1.03	1.64	2.35	1.08	1.00

Later, fatal accident involvement rates per vehicle miles traveled will be presented as a similar relative risk. The calculation is the same. The accident rate (trucks involved per vmt) in an individual category is divided by the overall accident rate to produce a relative risk scaled to an overall value of 1.0.

This initial work focuses on common variables in both the TIFA data and the 1992 Truck Inventory and Use Survey so that the relative risk of fatigue based on the registered vehicle population and vehicle miles traveled can also be calculated. For these variables, three rates, or relative risks, can be formed:

1. Fatigue in fatal accident involvement per vehicle miles traveled

2. All fatal accident involvement per vehicle miles traveled

3. Fatigue fatal accident involvement per all fatal accident involvement

The three are related as:

Fatal fatigue involvement/vmt = (all fatal involvement/vmt) x
(fatal fatigue involvement/(all fatal involvement)

This is equivalent to:

Relative risk of fatigue in a fatal accident = (relative risk of fatal accident involvement) x
(relative risk of fatigue given fatal involvement)

The relative risk of fatigue per vehicle (driver) or per vehicle miles traveled is probably of primary interest. However, the necessary exposure data are available for only a few factors, trip distance, power unit type, and private/for hire. After that, we have only the accident data and can only calculate the last term, the risk of fatigue given fatal accident involvement. The exposure-based rates will illustrate the relationship (or lack of relationship) between relative risk based only on accident data and risk measures based on exposure.

Exposure data and rates based on exposure data are covered in the next Section, 1.2. This section covers all results based only on accident data. The following results are limited to fatal accidents. Information on non-fatal accidents in Texas is presented Section 1.1.3.

The first group of results is limited to variables that are available in both FARS/TIFA and the 1992 TIUS. The three variables are: trip distance, power unit type (straight/tractor), and carrier type (private/for hire). The sequence of figures is as follows:

Figure 6, Figure 7:	Trip distance (5 levels), 1994–1996
Figure 8, Figure 9:	Trip distance (5 levels) by Power Unit Type, 1994–1996
Figure 10, Figure 11:	Trip distance (3 levels), 1991–1996
Figure 12, Figure 13:	Trip distance (3 levels) by Power Unit Type, 1991–1996
Figure 14, Figure 15:	Trip distance and Power Unit type (6 levels) by Carrier Type, 1991–1996
Figure 16, Figure 17:	Trip distance and Power Unit type (6 levels) by Truck/Nontruck, 1991–1996

The pairs of figures on the following pages show the prevalence (or percent distribution) of all trucks involved in fatal accidents on the top of the page and the subset of those trucks with fatigued drivers on the bottom of the page (as in Table 7and Table 6). The bottom figure shows the relative contribution of each category to the overall prevalence of fatigue. Comparison of the distributions on the top and bottom of each page gives a visual indication of the under- or over-involvement of fatigue in each category of the independent variables. The ratio of these percentages, the relative risk of fatigue given involvement in a fatal accident, is presented later in this section after all the prevalence results. Higher levels of relative risk imply an association between factors defining (or associated with) the categories of the independent variable and the risk of a fatigue related involvement in a fatal accident. Some observations from this first group of results on prevalence follow.

Trip Distance. The definition of this variable in the TIFA file is taken from the Truck Inventory and Use Survey. The categories are based on the trip distance in one direction, and not the round-trip distance. For application in TIFA, it is defined as the *intended* one-way trip distance in order for the categories to be compatible with TIUS. Thus, in the TIFA file, the accident must have occurred at some distance less than the intended one-way distance. Hours of driving since the last 8-hour break are recorded in a separate variable and time of day is also available from the FARS record, but no comparable exposure data are available on these variables. Results on time of day and hours driving from the accident data will be presented after the current group of variables.

The current 5-level version of the trip distance variable is available since 1994 in TIFA. Even though TIUS adopted this version for the 1992 survey, TIFA did not incorporate it until 1994. The 3-level version used in the earlier TIUS was used in TIFA starting with the 1991 file. The major observation has already been stated: the greatest portion (prevalence) of the fatigue cases, 36.6 percent, are in the trip distance greater than 500 miles category, whereas only 15.5 percent of *all* trucks involved in fatal accidents are on trips of more than 500 miles. Thus, fatigue is over-represented in trips over 500 miles by a factor of 2.35, the ratio of these two percentages. These relative risk estimates based on fatal accident involvement will be presented after the prevalence data. Essentially the same pattern is shown in the 3-level and 5-level versions of this variable. The 3-level version is more useful because 6 years of TIFA data are available as compared to only 3 with the 5-level version.

Power Unit type and Trip Distance. Truck configuration for this study is based only on the power unit. This classification is most accurate in the TIFA and TIUS files. In practice, it is essentially the same as a single-unit versus combination vehicle split. Again, the greatest prevalence of fatigue is on the longest trips and these trips are overwhelmingly taken by tractors. Based on the 1991–1996 TIFA data, only 20 percent of the truck driver fatigue coded is for straight truck drivers.

Carrier Type. Fatigued drivers work primarily for for-hire carriers. Only 30 percent of the fatigued truck drivers involved in fatal accidents work for private carriers. In comparison, 43 percent of all medium and heavy truck drivers involved in fatal accidents work for private carriers. The relative risk of fatigue for private and for-hire carriers will be addressed later.

Truck and Nontruck Fatalities. This tabulation is somewhat different. Here the split is based on whether the fatalities were truck occupants or not. If the *only* fatalities in the accident were truck occupants, then it is categorized as a "truck" fatal involvement. If anyone other than a truck occupant received fatal injuries in the accident, then it is categorized as a "nontruck" fatal involvement. These two figures do not address factors associated with fatigue, but simply address the victims of fatigued truck drivers in fatal accidents. First, looking at all fatal accidents involving a medium or heavy truck, nearly 90 percent of the fatalities are parties other than the truck occupants. Most of these are occupants of passenger cars and other vehicles involved in the accident with the truck. But when the truck driver is coded as fatigued, this situation reverses dramatically. Seventy percent of the truck driver fatigue involvements result only in fatalities to truck occupants. Only 30 percent result in fatal injury to nontruck occupants. This is largely a reflection of the fact that most fatal fatigue accidents are single vehicle accidents. It may be that fatigue frequently produces ran off the road (single vehicle) accidents, or it may be related to the association of fatigue and night travel when traffic volumes are low.

In any event, the FARS/TIFA data do not provide any evidence that truck driver fatigue plays a significant role in fatalities among occupants of other vehicles involved in collisions with medium and heavy trucks. In fact, looking at truck/nontruck two-vehicle fatal collisions, fatigue is coded for the nontruck driver much more often than for the truck driver, 2.4 percent versus 0.9 percent (Blower, 1998).

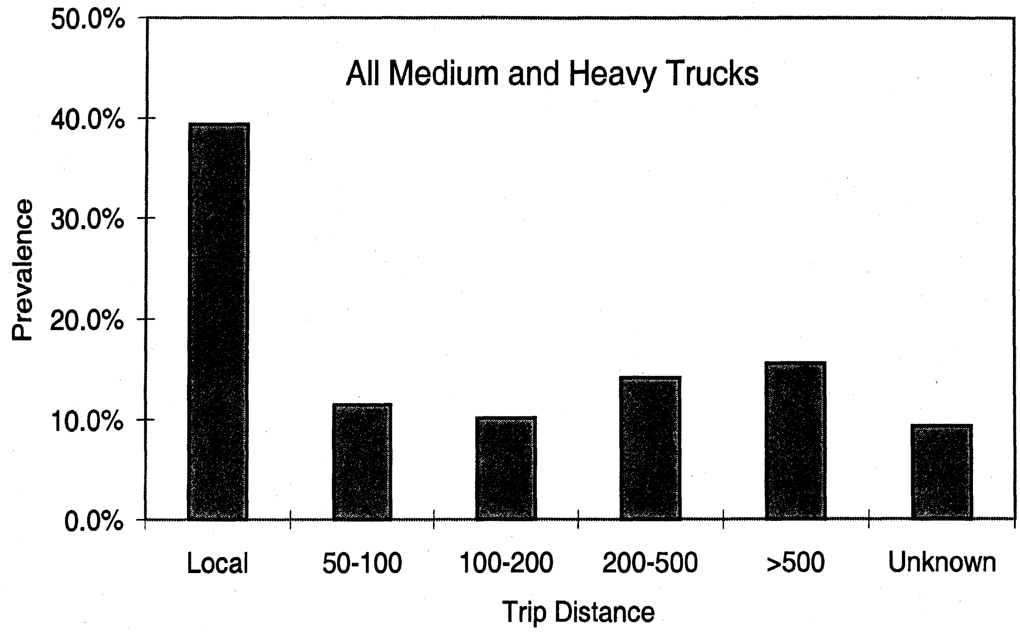

Figure 6: Percent Distribution by Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996

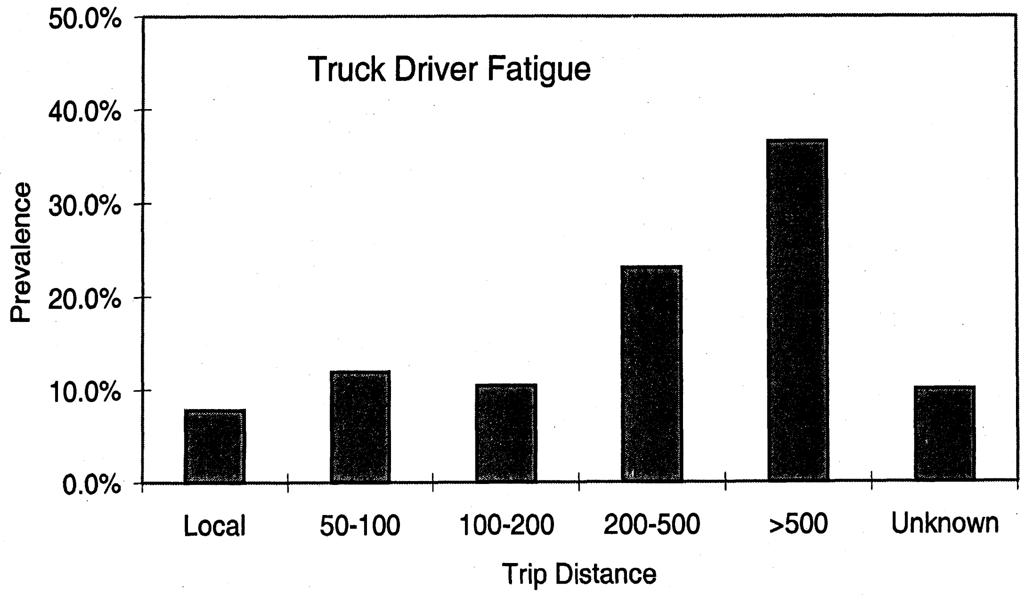

Figure 7: Percent Distribution of Truck Driver Fatigue by Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996

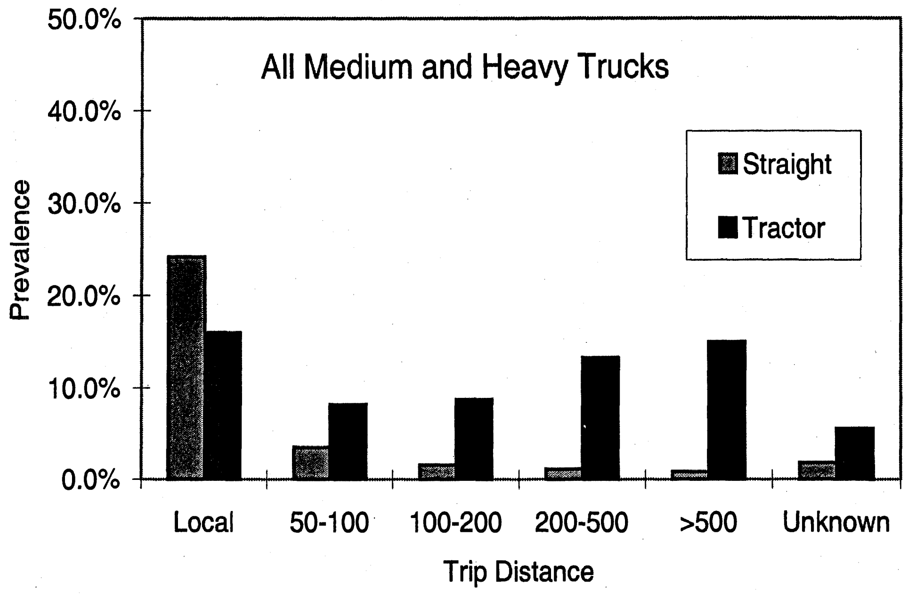

Figure 8: Percent Distribution by Power Unit Type and Trip Distance (5 level) Trucks Involved in Fatal Accidents 1994-1996

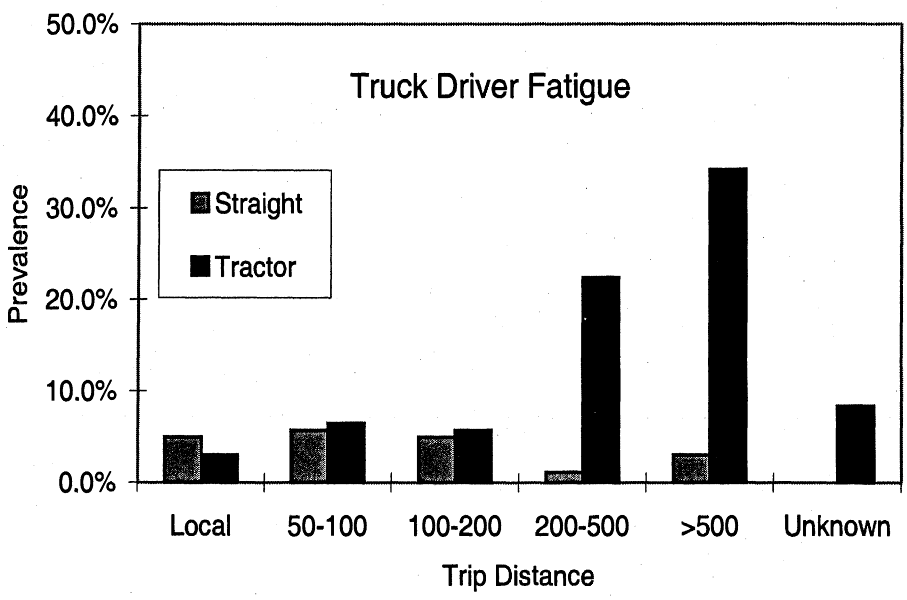

Figure 9: Percent Distribution of Truck Driver Fatigue by Power Unit Type and Trip Distance (5 level)Trucks Involved in Fatal Accidents 1991-1996

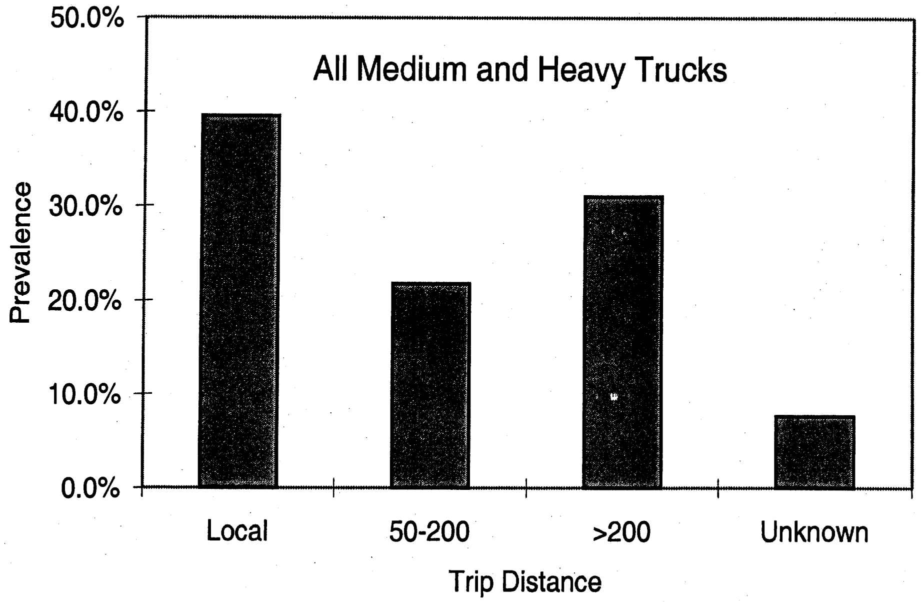

Figure 10: Percent Distribution by Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996

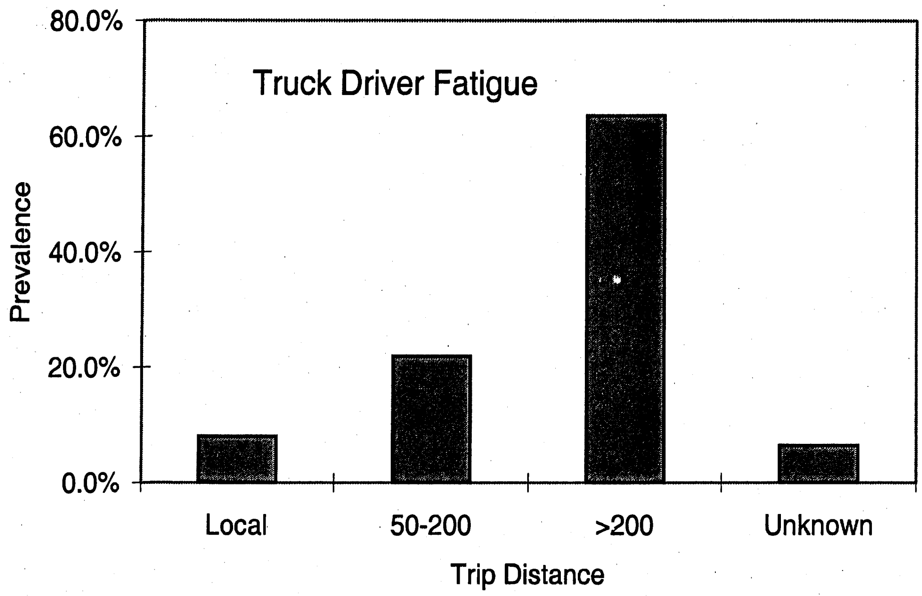

Figure 11: Percent Distribution of Truck Driver Fatigue by Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1994-1996

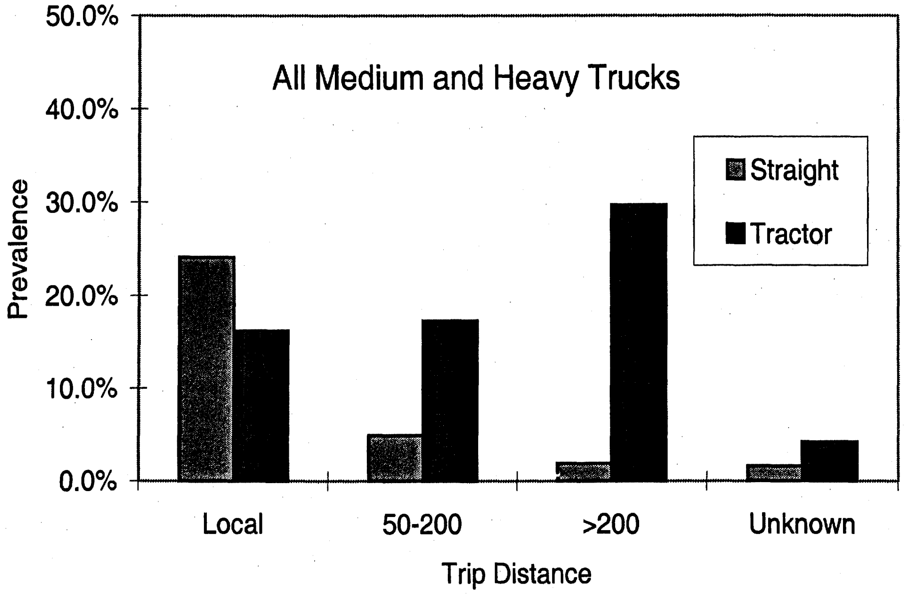

Figure 12: Percent Distribution by Power Unit Type and Trip Distance (3 level) Trucks Involved in Fatal Accidents 1991-1996

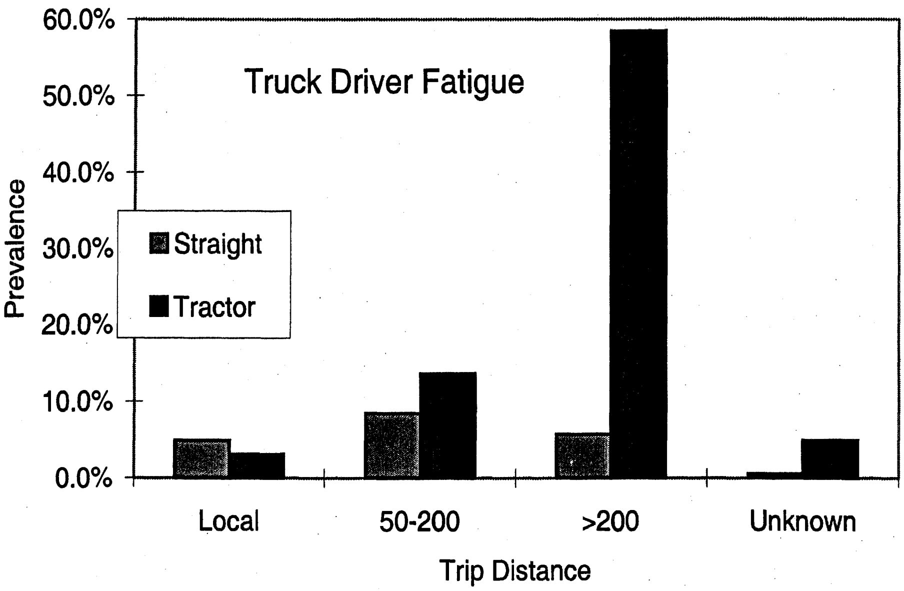

Figure 13: Percent Distribution of Truck Driver Fatigue by Power Unit Type and Trip Distance (3 level), Trucks Involved in Fatal Accidents 1991-1996

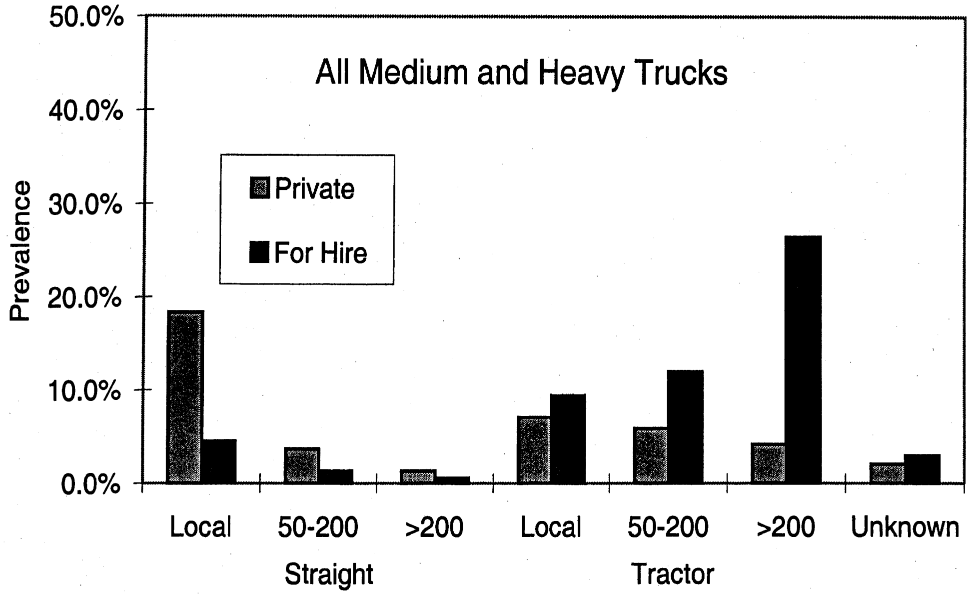

Figure 14: Percent Distribution by Power Unit Type and Trip Distance (6 levels) by Carrier Type, Trucks Involved in Fatal Accidents 1991-1996

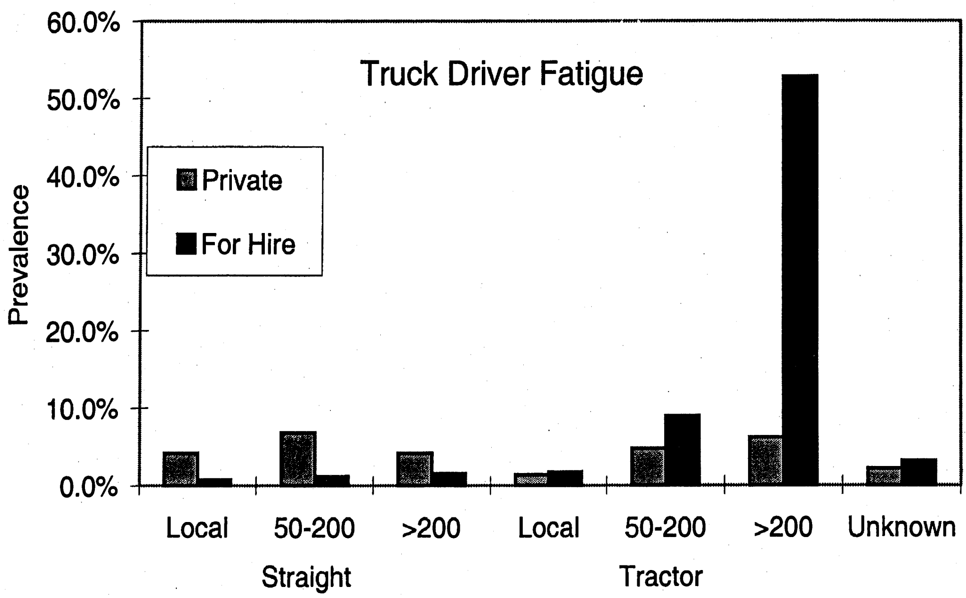

Figure 15: Percent Distribution of Truck Driver Fatigue by Power Unit Type and Trip Distance (6 levels) by Carrier Type, Trucks Involved in Fatal Accidents 1991-1996

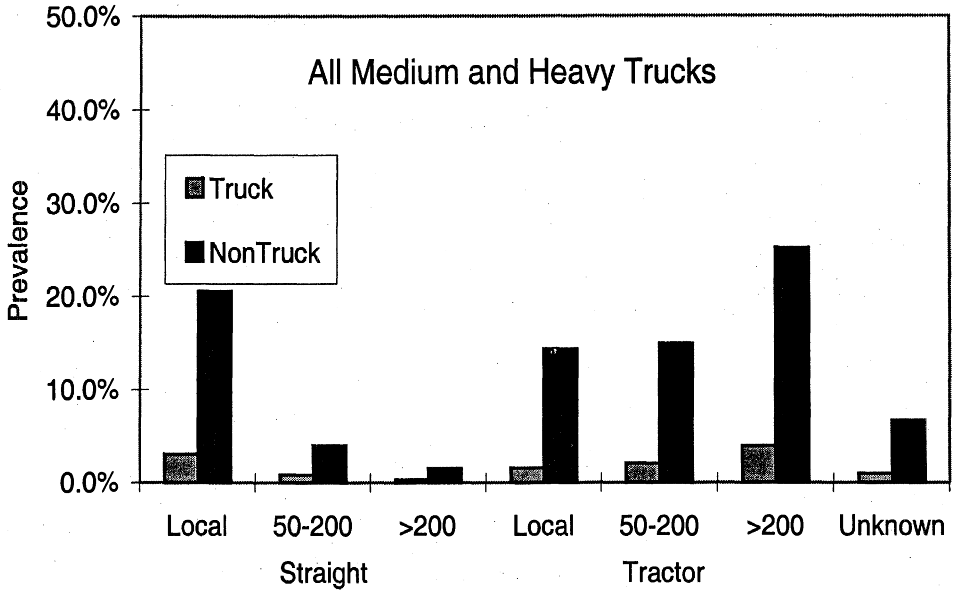

Figure 16: Truck versus Nontruck Fatalities: Percent Distribution by Power Unit Type and Trip Distance (6 levels) Trucks Involved in Fatal Accidents 1991-1996

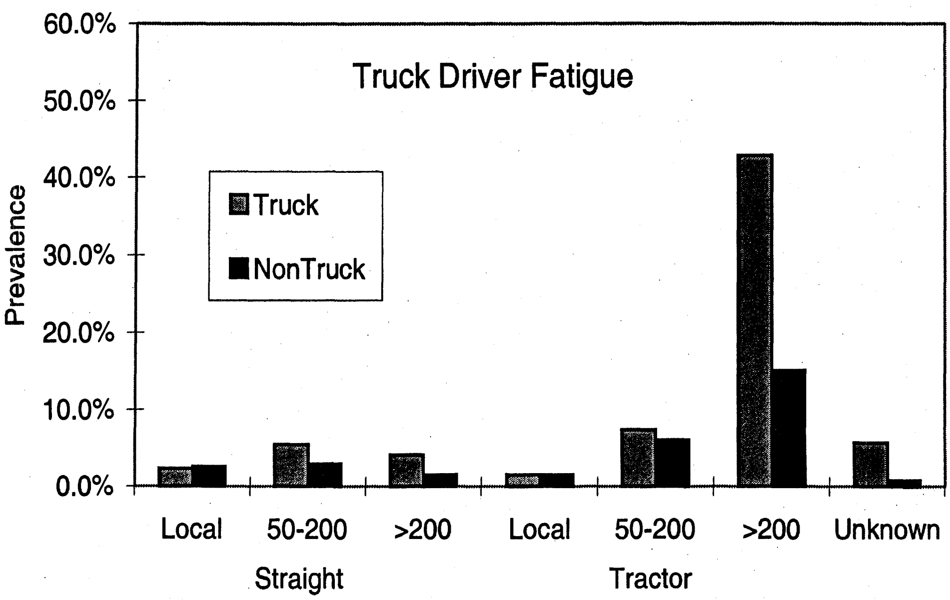

Figure 17: Truck versus Nontruck Fatalities: Percent Distribution of Truck Driver Fatigue by Power Unit Type and Trip Distance (6 levels) Trucks Involved in Fatal Accidents 1991-1996

Time of Day

This series of figures focuses on one variable: time of day. No exposure data are available for time of day, so all results come from the TIFA files. This series maintains the full detail of 24 hourly categories. In order to get a maximum sample for this analysis, results from 16 years of TIFA data, 1981 to 1996, were combined. A few comparisons showed no significant differences in results from the earlier years as compared to later years. This was also illustrated in the previous material on the coding of fatigue by state. The 16 years of TIFA data include 79,352 medium and heavy trucks involved in fatal accidents. Of these, fatigue was coded as a contributing factor for 1,653 truck drivers, or 2.1 percent. This percentage is a little higher than the 1.9 percent for the years 1991 to 1996. This difference is a result of the slight downward trend observed in the plot of fatigue by year in the earlier materials. The annual average over the 16 years is 103 truck drivers per year with fatigue coded as a contributing factor out of an annual average of 4,959 medium and heavy trucks involved in fatal accidents.

Missing data on time of day reduces the available sample by only 0.1 percent. Missing data on other variables examined further reduces the data by usually only a few percent. For example, missing data on power unit type (straight truck vs. tractor) is 1.8 percent over the 16 years.

Prevalence is presented as a percentage. The sum of all bars on every figure is 100 percent. This holds when another variable is used to divide the data, such as straight trucks versus tractors. Overall percentages are shown so that the sum of all the straight truck bars plus the tractors is 100 percent. This approach maintains the relative proportions of straight trucks versus tractors while also illustrating the pattern with time of day. Figures in this section are presented in pairs, two on a page. The top figure shows the distribution (prevalence) of all medium and heavy trucks involved in fatal accidents and the bottom figure is the distribution of all medium and heavy trucks involved in fatal accidents where truck driver fatigue was coded as a contributing factor. The top figure is shown only for reference, or perspective, to illustrate the overall pattern of fatal accidents involving medium and heavy trucks. For many factors, the distribution of all trucks involved in fatal accident reflects the underlying exposure. The overall fatal accident involvement can be thought of as the product of the exposure amount multiplied by the risk of involvement in a fatal accident per unit exposure. One could observe in the earlier material using exposure estimates from TIUS, that the variations in risk were often less than the variation in exposure, so that the underlying exposure pattern is visible in the accident experience. Of course, this is not always the case, and without exposure data, one cannot know for sure. However, the variation in exposure by time of day is believed to be sufficiently large to be visible in the overall fatal accident experience of medium and heavy trucks.

While the top figure is intended to provide a reference, or perspective, the bottom figure in this series is of more immediate relevance. It shows only truck driver fatigue in fatal accidents. This is the accident subset of interest, and these figures show the situations where truck driver fatigue occurs most often. The following series illustrates other factors in combination with time of day. As a starting point, the first pair of figures shows the distribution by time of day for all medium and heavy trucks involved in fatal accidents from 1981 to 1996. All trucks involved in fatal accidents are shown in the top figure (Figure 18) and the subset of those where the truck driver has fatigue coded as a contributing factor are shown on the bottom of the page (Figure 19). The difference in these two distributions is striking. Whereas exposure is believed to dominate the first, clearly the variations in the risk of fatigue dominate the pattern of fatigue-related involvements. Figure 19 follows the circadian pattern.

Looking ahead to the last series of figures on risk, the measure used here is simply a comparison of the top and bottom prevalence figures. For example, if the midnight hour contains 2.5 percent of all trucks involved in fatal accidents (from Figure 18) and 5 percent of the truck fatigue involvements (from Figure 19), then the relative risk of fatigue is 2 (5.0/2.5) for the midnight hour, given involvement in a fatal accident. This calculations is presented in the last series on relative risk per involvement starting with Figure 46.

The following additional factors are illustrated with time of day in the remaining pairs of figures in this series:

Figure 20, Figure 21: Power Unit Type (straight trucks versus tractors), 1981–1996
Figure 22, Figure 23: Truck Occupant Fatalities versus Nontruck Fatalities, 1981–1996
Figure 24, Figure 25: Trip Distance (local versus over the road), 1981–1996
Figure 26, Figure 27: Operating Authority (interstate versus intrastate), 1981–1996
Figure 28, Figure 29: Carrier Type (private versus for hire), 1981–1996
Figure 30, Figure 31: Carrier Type For Interstate Carriers Only, 1981–1996
Figure 32, Figure 33: Power Unit Type And Trip Distance, 1981–1996

Observations on this series of results follow.

Power Unit type. As shown before, the majority of fatigue coded in the FARS/TIFA data is for tractor drivers. Even though the magnitude of fatigue is much smaller for straight truck drivers, it still reflects the circadian pattern. Overall, this series of figures illustrates the pervasive impact of the circadian pattern on fatigue for truck drivers. To the extent that the distribution of all fatal accident involvement by time of day reflects the underlying exposure, it is evident that straight trucks operate predominately during the day. Tractor involvements drop off at night by only a third or so in comparison to daytime levels, implying more night exposure than straight trucks.

Truck and Nontruck Fatalities. Here the categories separate fatal accident involvement where the only fatalities where truck occupants from those resulting in fatalities to other parties in the accident. As noted earlier, the majority of fatalities resulting from truck driver fatigue are truck occupants. The distribution of all fatal involvement appears to reflect the underlying exposure. Truck involvement resulting in nontruck fatalities reflects substantially more daytime travel, while the truck fatality subset shows a more uniform pattern by time of day. For each subset, fatigue follows the circadian rhythm.

Trip Distance. The two trip distance categories show the predominant daytime operation for local trips (in the top figure) and the more uniform distribution by time of day for the over the road (long haul) trips. However, fatigue follows the circadian pattern. Not the prominent 3pm peak evident for the long-haul truck drivers on the bottom figure.

Operating Authority. Similar results are shown for truck operated by interstate carriers as compared to intrastate. The experience for intrastate carriers is very similar to that for local trips in the previous figures. Trucks operated by interstate carriers are involved in 73 percent of all fatal accidents and 89 percent of the truck driver fatigue involvement. This result is apparently die in part to the greater nighttime operation by interstate carriers.

Carrier Type. Similar insight on the difference between private and for-hire carriers is provided by the time of day distributions. Looking at the top figure, for-hire carriers appear to operate much more at night than private carriers. This is true even when the comparison is limited to interstate carriers in the next pair of figures. The circadian pattern is always evident in the fatigue subset.

Power Unit type and Trip Distance. The final pair of figures shows four categories formed by the combination of straight trucks versus tractors with local versus over the road trips. The results are consistent with the trends each factor showed separately. As has been the case in every figure in this series, the fatigue follows the circadian rhythm.

The relation of time of day and fatigue is pervasive. It is clearly reflected in every subset examined.

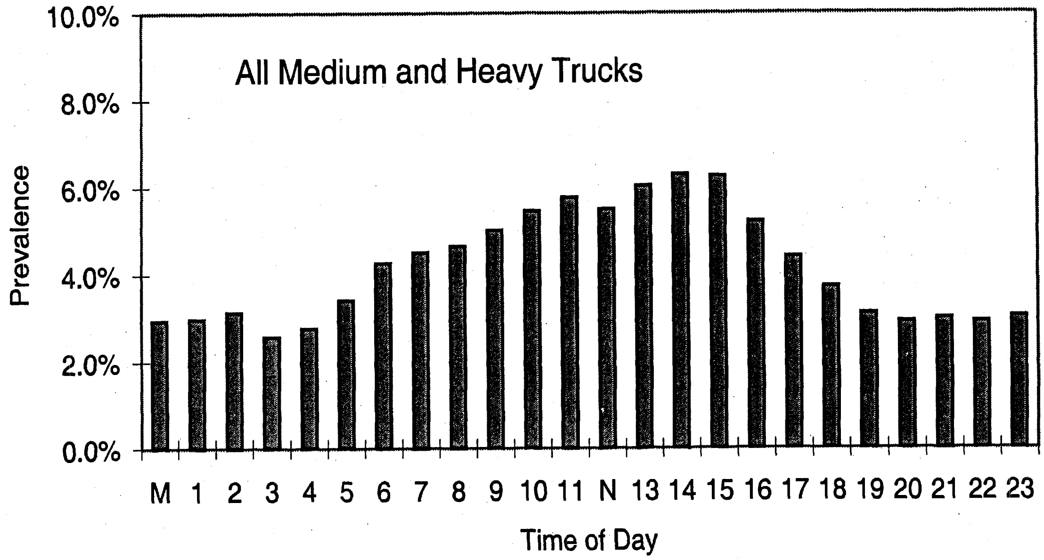

Figure 18: Time of Day Distribution for All Medium and Heavy Trucks Involved in Fatal Accidents, 1981-1996

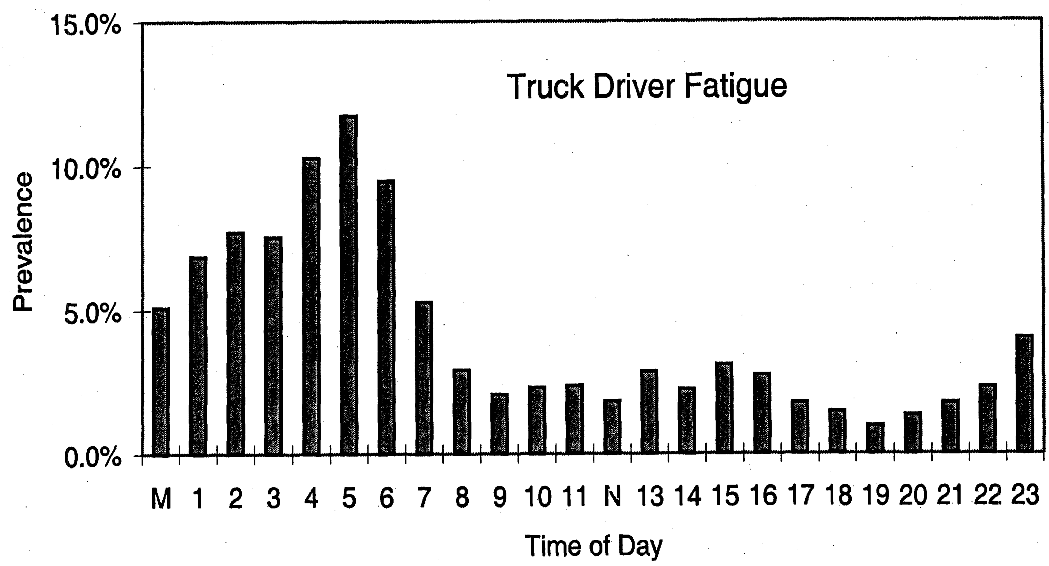

Figure 19: Time of Day Distribution of Truck Driver Fatigue for All Trucks Involved in Fatal Accidents 1981-1996

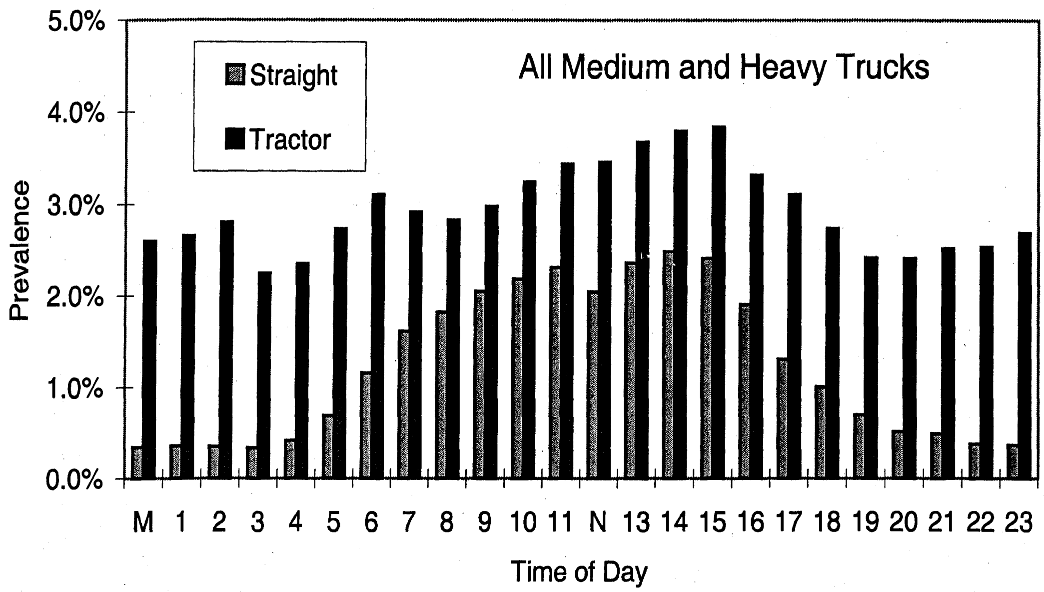

Figure 20: Time of Day Distribution by Power Unit Type
Trucks Involved in Fatal Accidents 1981-1996

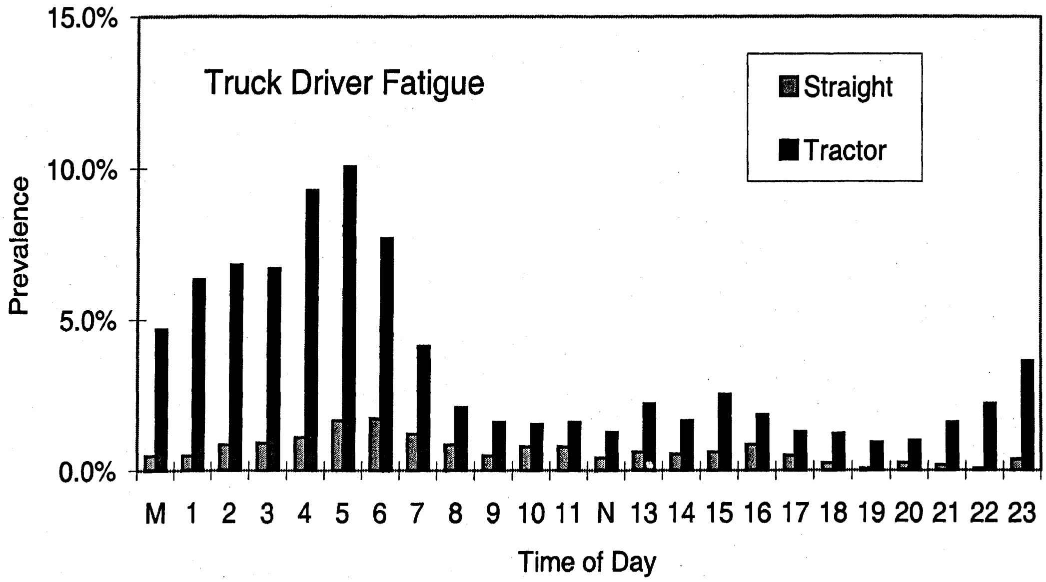

Figure 21: Time of Day Distribution of Truck Driver Fatigue by Power Unit Type
Trucks Involved in Fatal Accidents 1981-1996

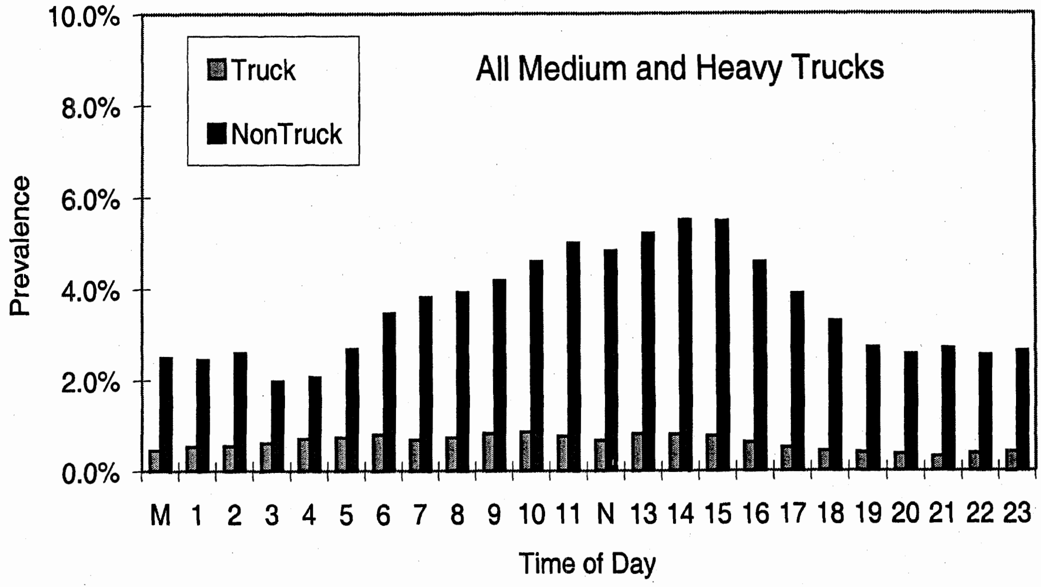

Figure 22: Time of Day Distribution for Truck Occupant and Nontruck Fatalities Trucks Involved in Fatal Accidents 1981-1996

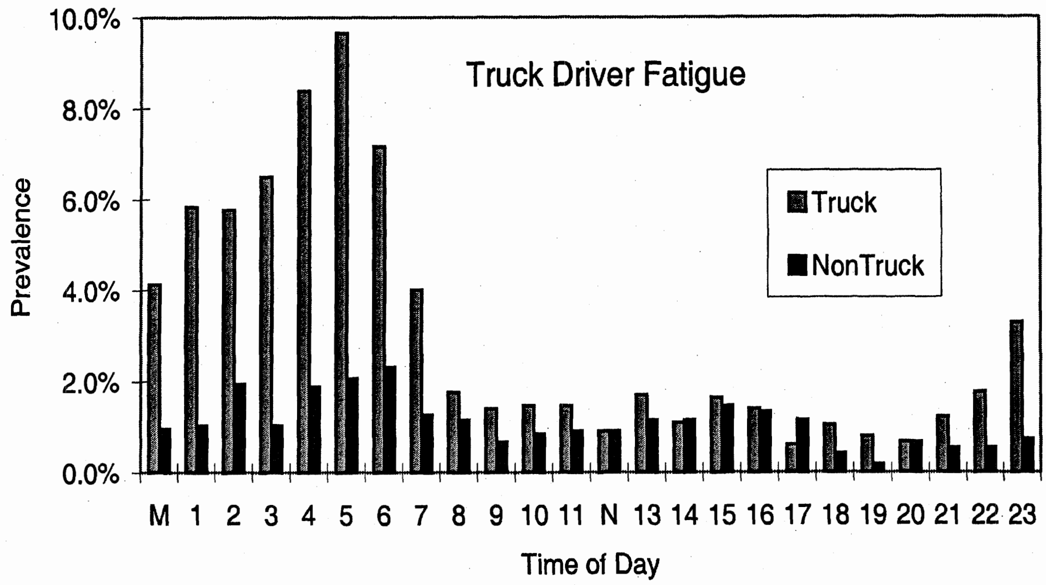

Figure 23: Time of Day Distribution of Truck Driver Fatigue for Truck and Nontruck Fatalities Trucks Involved in Fatal Accidents 1981-1996

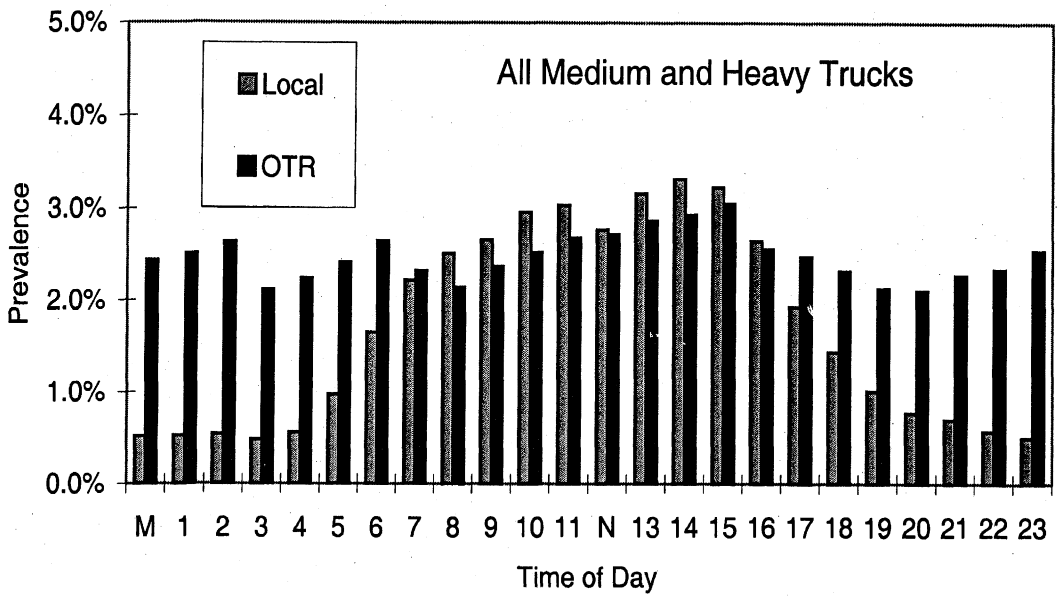

**Figure 24: Time of Day Distribution by Trip Distance
Trucks Involved in Fatal Accidents 1981-1996**

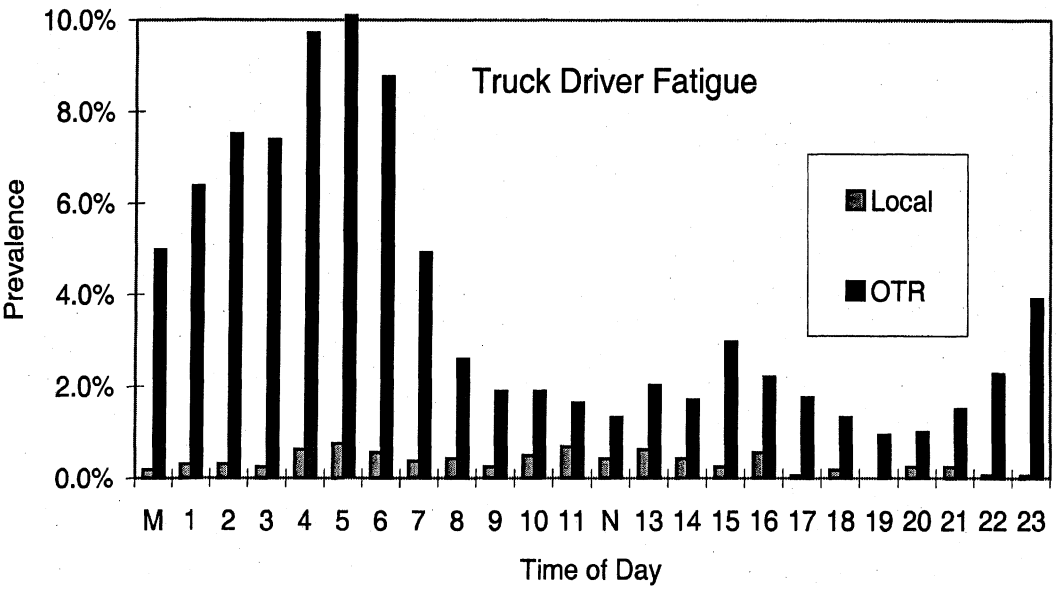

**Figure 25: Time of Day Distribution of Truck Driver Fatigue by Trip Distance
Trucks Involved in Fatal Accidents 1981-1996**

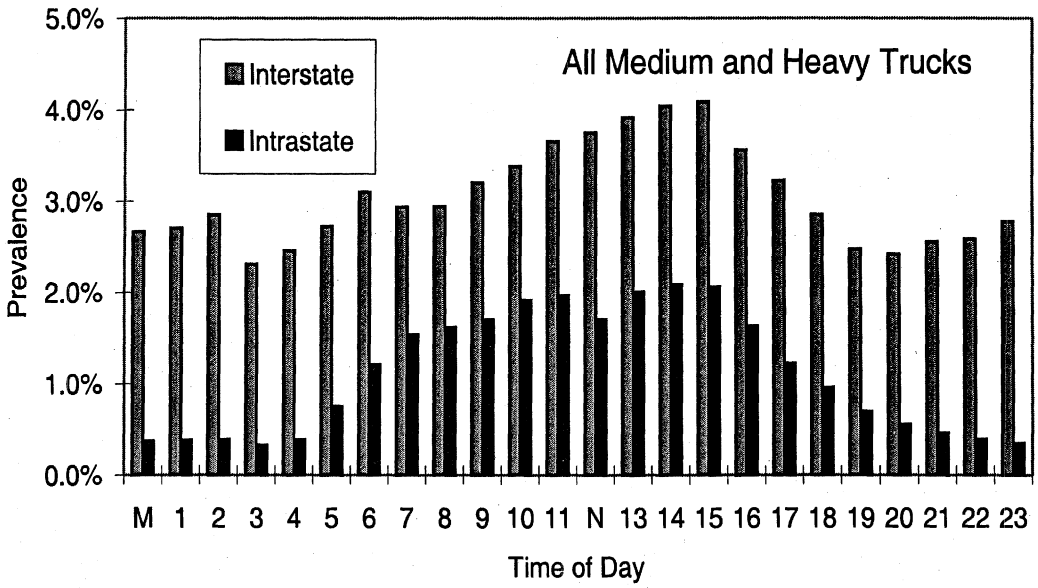

Figure 26: Time of Day Distribution by Operating Authority Trucks Involved in Fatal Accidents 1981-1996

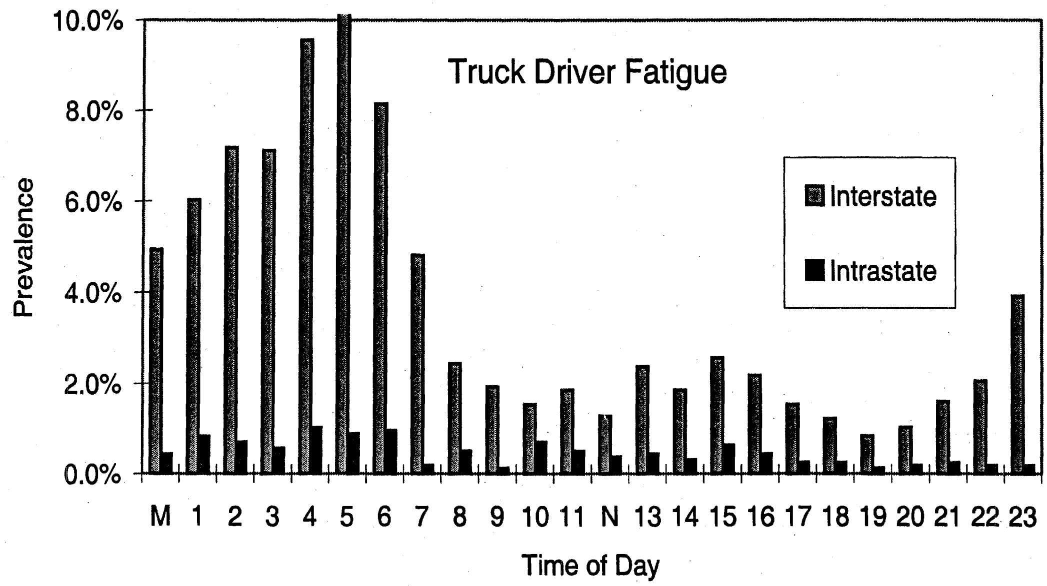

Figure 27: Time of Day Distribution of Truck Driver Fatigue by Operating Authority Trucks Involved in Fatal Accidents 1981-1996

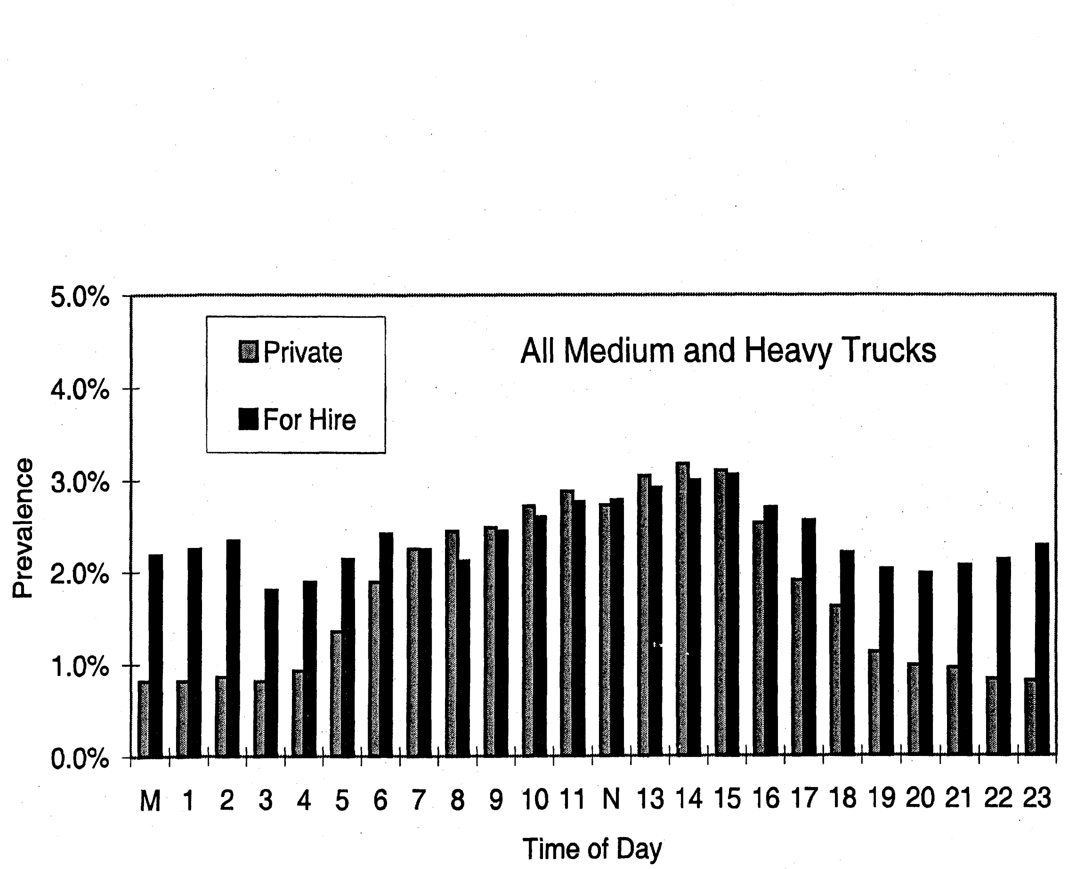

Figure 28: Time of Day Distribution by Carrier Type
Trucks Involved in Fatal Accidents 1981-1996

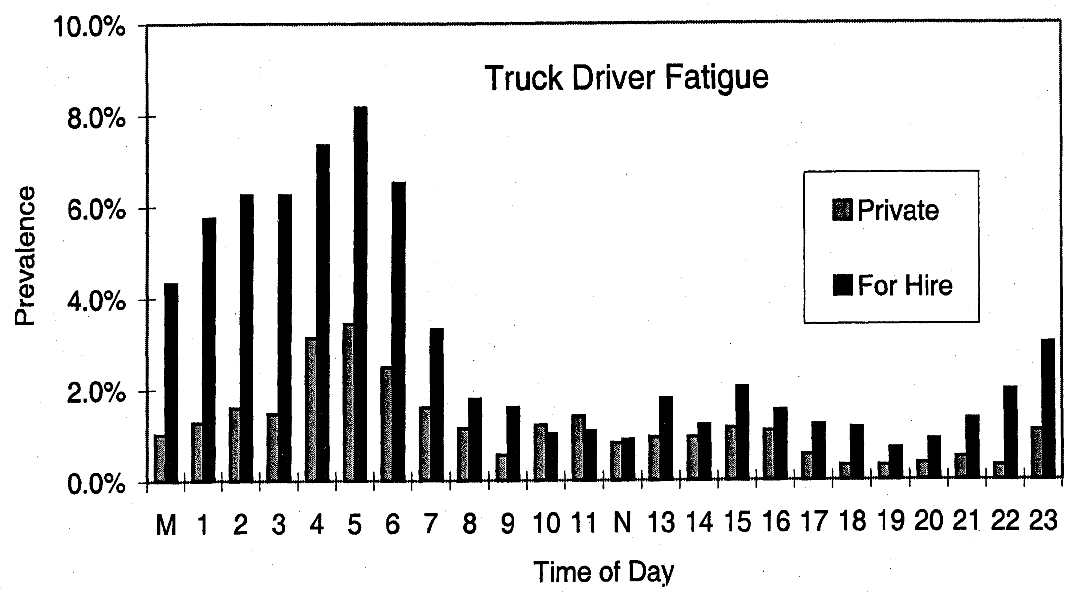

Figure 29: Time of Day Distribution of Truck Driver Fatigue by Carrier Type
Trucks Involved in Fatal Accidents 1981-1996

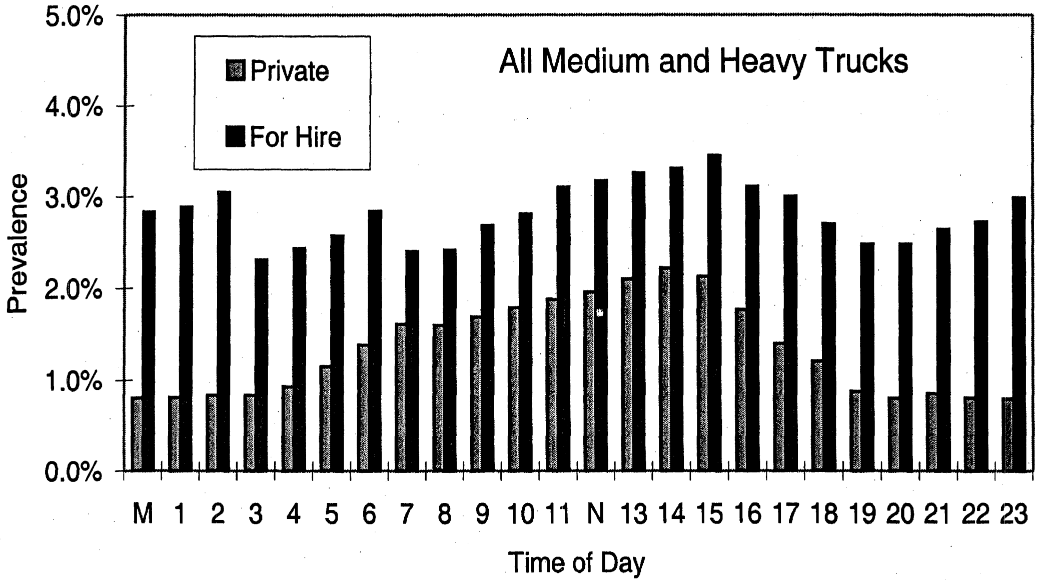

Figure 30: Time of Day Distribution by Carrier Type—Interstate Only Trucks Involved in Fatal Accidents 1981-1996

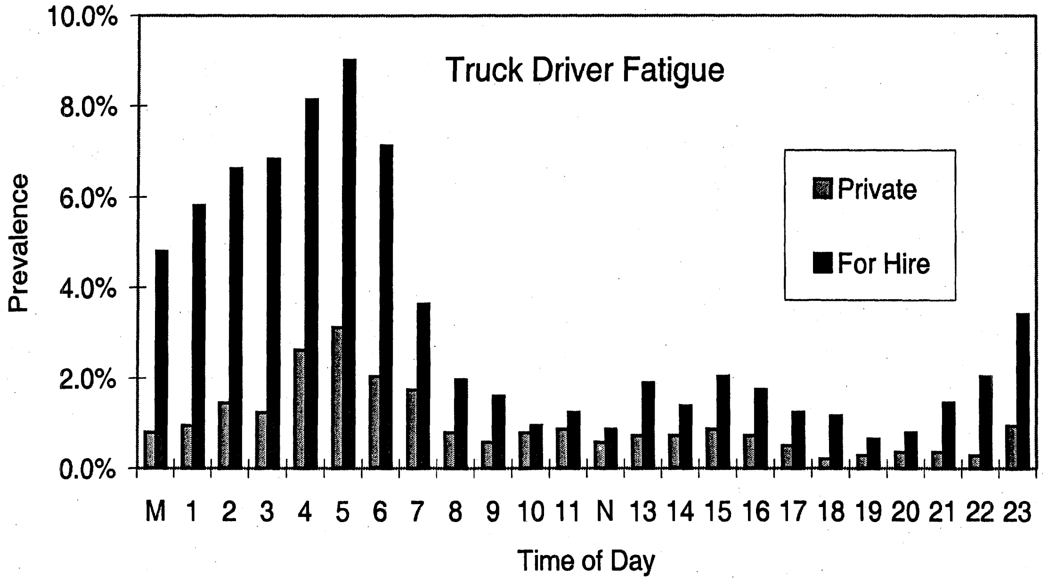

Figure 31: Time of Day Distribution of Truck Driver Fatigue--Interstate Carriers Trucks Involved in Fatal Accidents 1981-1996

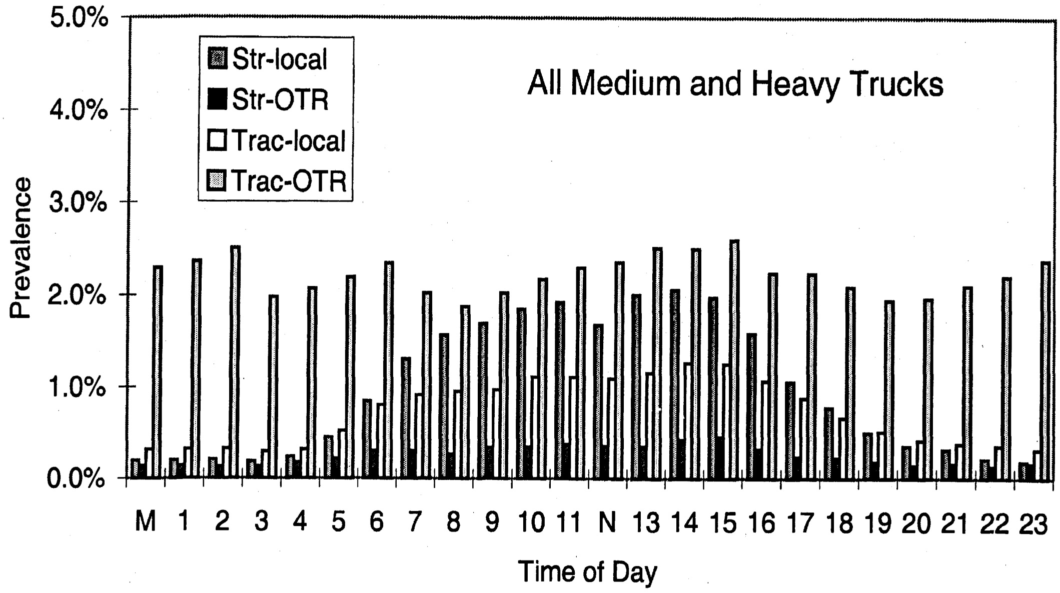

Figure 32: Time of Day Distribution by Power Unit Type and Trip Distance Trucks Involved in Fatal Accidents 1981-1996

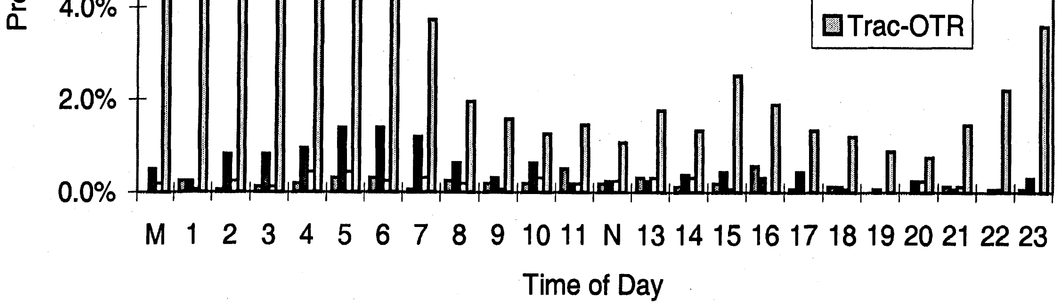

Figure 33: Time of Day Distribution of Truck Driver Fatigue by Power Unit Type and Trip Distance, Trucks Involved in Fatal Accidents 1981-1996

Hours Driving

This series of figures focuses on the number of hours driving at the time of the accident. No exposure data are available, so all results come from the TIFA files. Again, 16 years of TIFA data are combined, 1981 to 1996. The origin of this variable in the TIFA file is Question 11E on the MCS 50-T accident report that was submitted by interstate motor carriers. The question asked for the "hours actually driving since the last period of 8 consecutive hours off duty." A category was provided for each hour up to 12, and an additional category for "not applicable." No space was provided on the form to indicate hours driving greater than 12. Since the form was filed by the carrier, it is not likely they would have reported driving over 12 hours. From 1980 through 1992, about one third of the data in TIFA came from the MCS 50-T form. The remainder was collected by telephone interview. Since 1993, all the TIFA supplementary data is collected by telephone interview, including this question.

The interview source is still often the owner or driver of the truck, so one would not expect complete reporting for hours driving beyond the legal limit. However, the survey form provided space for any response and driving times over 12 hours are sometime reported. In some cases the information may come from an investigating officer. Sometimes respondents refuse to answer this question. Consequently, missing data on this variable is much higher than any of the other variables used for this analysis, about 25 percent in the years 1991 to 1996. Cases with missing data on hours driving have been excluded for this series of figures. This results in some loss of sample size. Cases with missing data on hours driving at the time of the accident have about the same proportion of truck driver fatigue, 2 percent, as in the overall file. However, one can expect some bias even in the complete data. The results are likely to under estimate the effect of driving time since longer driving time, particularly over 12 hours are under-reported. The following results are provided in light of this caveat.

The following additional factors are illustrated with hours driving in the remaining pairs of figures in this series:

Figure 34, Figure 35: Hours Driving, 1981–1996
Figure 36, Figure 37: Power Unit Type (straight trucks versus tractors), 1981–1996
Figure 38, Figure 39: Trip Distance (local versus over the road), 1981–1996
Figure 40, Figure 41: Operating Authority (interstate versus intrastate), 1981–1996
Figure 42, Figure 43: Carrier Type (private versus for hire), 1981–1996
Figure 44, Figure 45: Power Unit Type And Trip Distance, 1981–1996

The results on hours driving at the time of the accident reveal the complexity of fatigue issues. Figure 34, the distribution of hours driving for all medium and heavy trucks involved in a fatal accident, illustrates an essential fact. The majority of accidents happen after only a few hours of driving. More than 25 percent occur in the first hour. Two-thirds occur in the first 4 hours. This pattern is driven by exposure, not risk. The most exposure necessarily takes place in the first hour because every trip begins with the first hour. One can't drive the second hour without having driven the first. We don't have exposure data by hours driven, so we don't know how many drivers stop after the first, second, or tenth hour. However, we do know that the exposure distribution must be continuously decreasing with hour driving.

For each successive hour driving, there must be fewer trips than for the previous hour. Consequently, accidents in the last hours of a trip will never be a large proportion of the total. Only about 4 percent of all medium and heavy truck drivers involved in a fatal accident reported driving more than 8 hours at the time of the accident. While, these numbers are believed to underestimate the true total, the nature of the exposure distribution will always keep the number of accidents after many hours driving a small proportion of the total, even with dramatic increases in risk with hour driving.

Looking at Figure 35, the majority of reported fatigue also occurs in the first few hours of driving. Half of all reported truck driver fatigue occurs in the first four hours of driving. Looking at the other end of the distribution, about 15 percent of the reported fatigue occurs after 8 hours of driving. While this figure implies a relative risk of fatigue of more than 3 (15/4) after 8 hours of driving, 15 percent is still a relatively small proportion of all accidents.

While these results confirm the generally accepted fact that fatigue increases with time on duty, they also illustrate that time on duty is not the only factor. As illustrated in the previous section, the time of day when each hour of driving takes place also influences the risk of fatigue. It is likely that there is a strong interaction between time of day and hours driving. The risk of fatigue when the eighth hour is driven at 4am is likely to be much higher than when the eighth hour is driven at 5pm. And the risk increase may be more than the product of the two marginal distributions. However, that issue was not examined in this current effort.

Furthermore, fatigue is cumulative. The amount of work and rest during the previous day and week also affect the level of fatigue during any hour of the current trip. However, no information on the previous work schedule is available for this study. Without such information, this study cannot quantify the cumulative effect of fatigue. Observations from the other factors that could be examined follow.

The distribution of hours driving for all truck drivers involved in fatal accidents illustrates that straight truck drivers generally take much shorter trips than tractor drivers, as would be expected. While this same result is evident in the comparison of local versus over the road trips, the difference is less.

The carrier variables show a similar pattern. There is a rather large difference in the distribution of hours driven for all truck drivers involved in fatal accidents (Figure 40). Intrastate carriers appear to take much shorter trips. However, in the subsequent comparison, there is not much difference between private carriers and for-hire carriers. Looking at Figure 43, for-hire carriers have the most reported fatigue during the fifth hour of driving. This also seems like an interesting finding that merits further study.

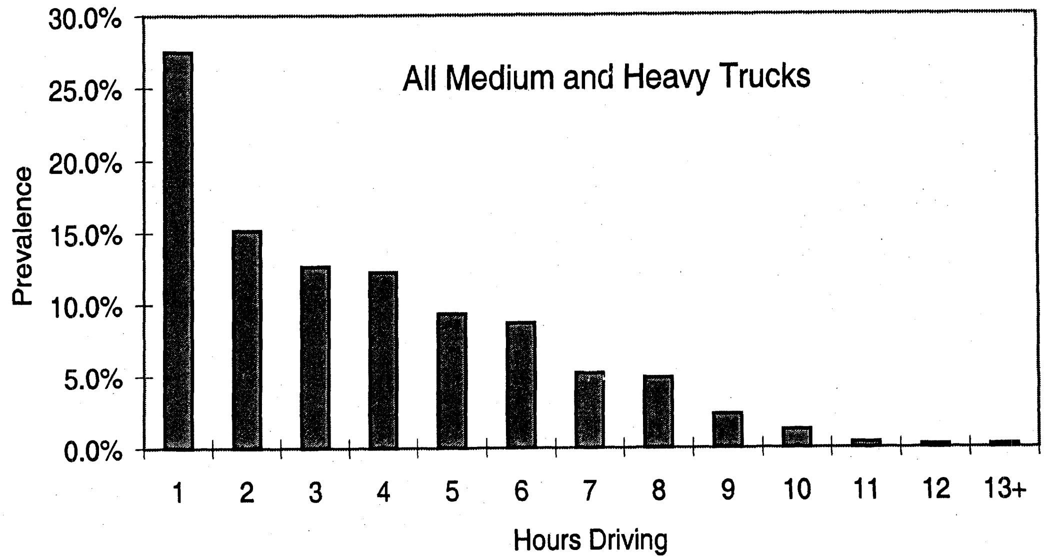

Figure 34: Hours Driving Distribution for all Medium and Heavy Trucks Trucks Involved in Fatal Accidents, 1981-1996

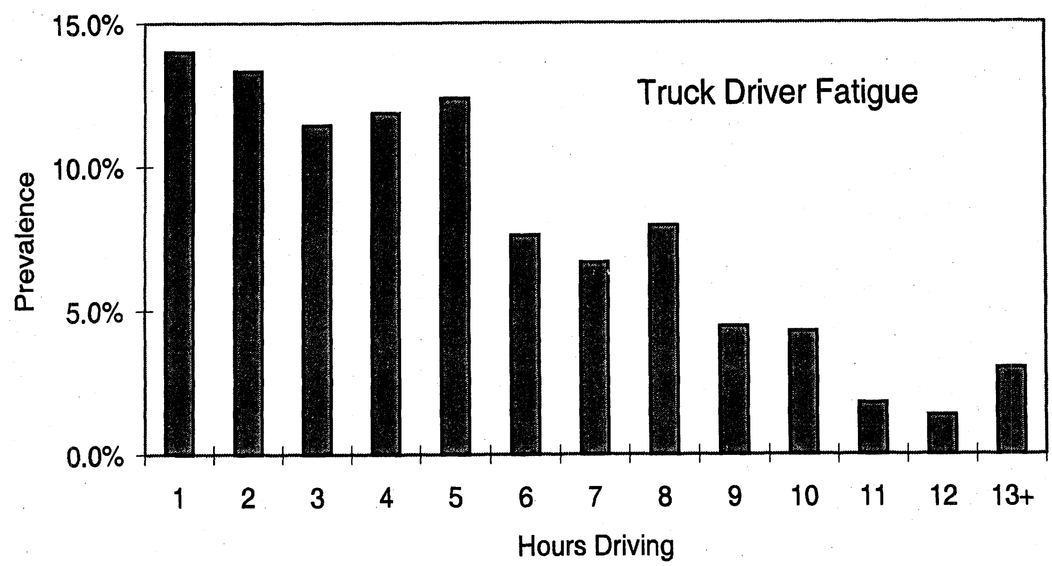

Figure 35: Hours Driving Distribution of Truck Driver Fatigue for all Trucks Trucks Involved in Fatal Accidents 1981-1996

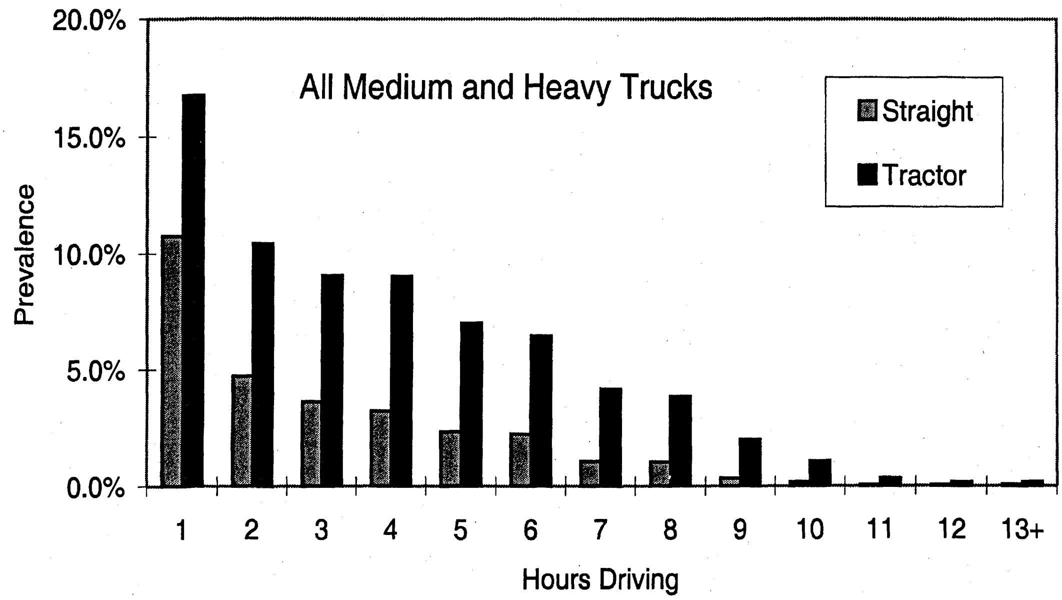

Figure 36: Hours Driving Distribution by Power Unit Type Trucks Involved in Fatal Accidents 1981-1996

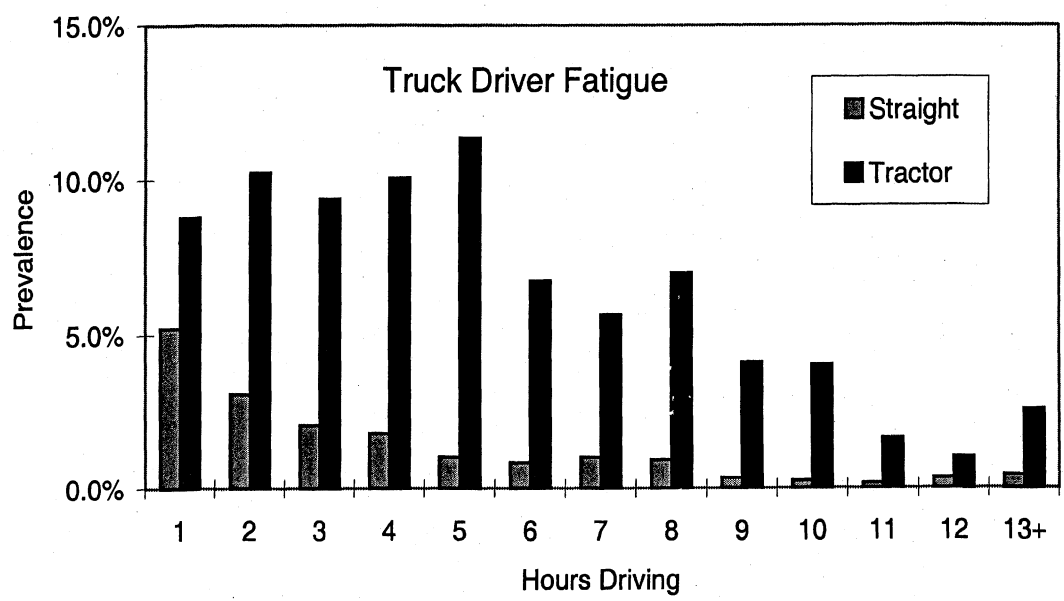

Figure 37: Hours Driving Distribution of Truck Driver Fatigue by Power Unit Type Trucks Involved in Fatal Accidents 1981-1996

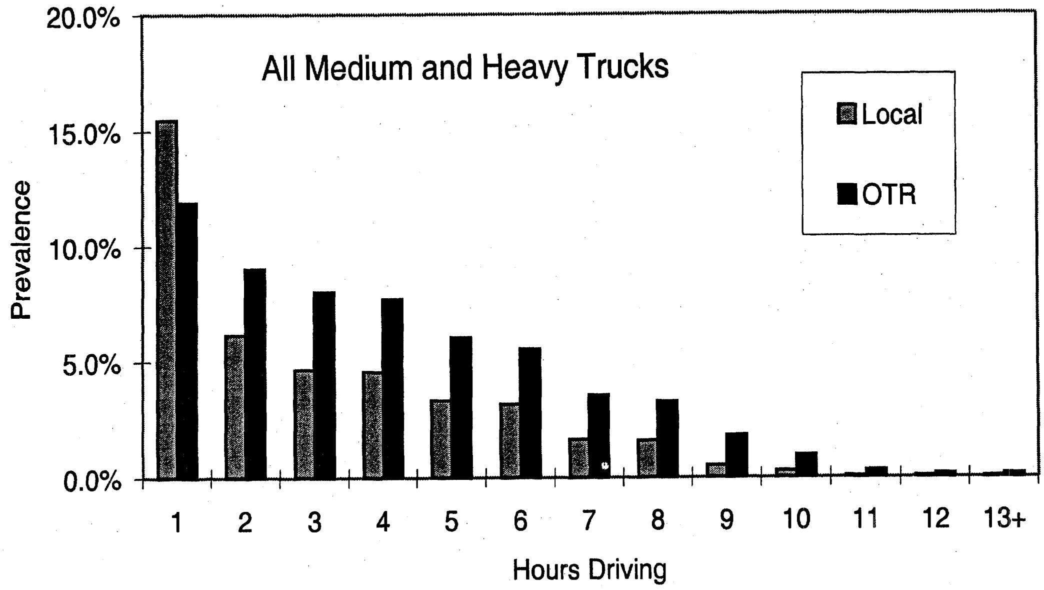

Figure 38: Hours Driving Distribution by Trip Distance Trucks Involved in Fatal Accidents 1981-1996

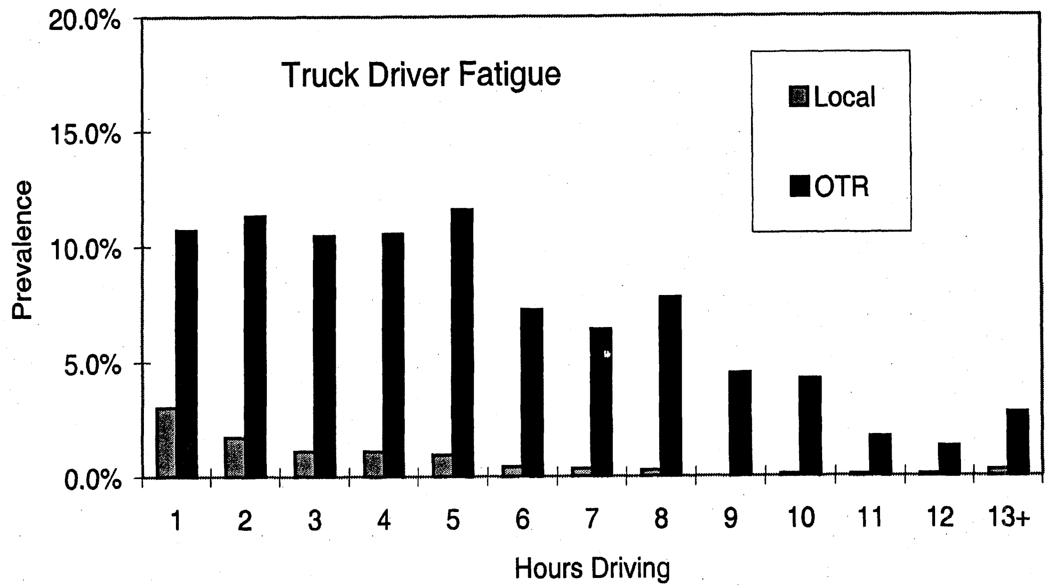

Figure 39: Hours Driving Distribution of Truck Driver Fatigue by Trip Distance Trucks Involved in Fatal Accidents 1981-1996

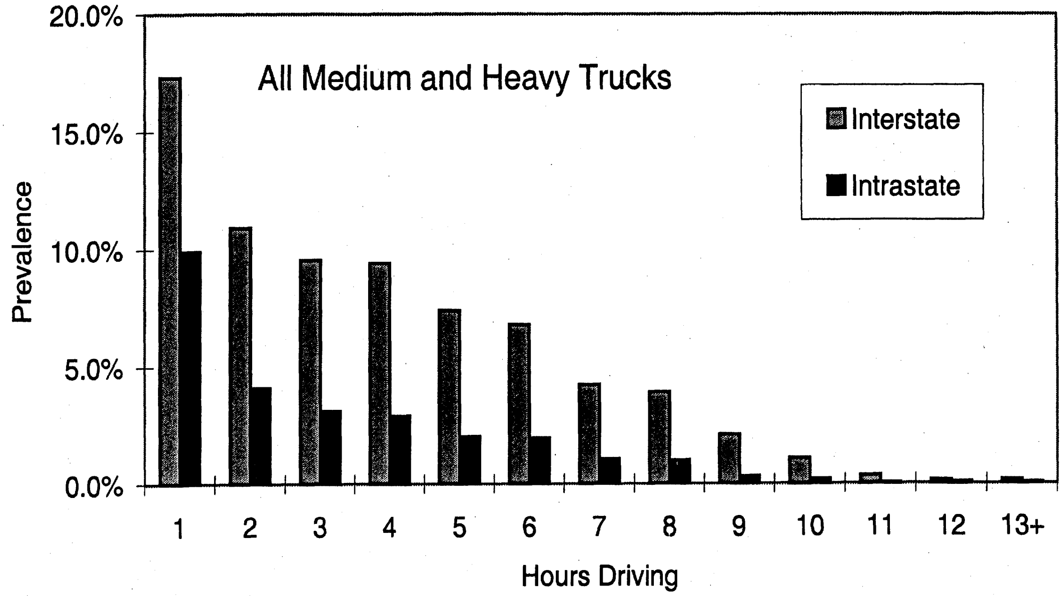

Figure 40: Hours Driving Distribution by Operating Authority Trucks Involved in Fatal Accidents 1981-1996

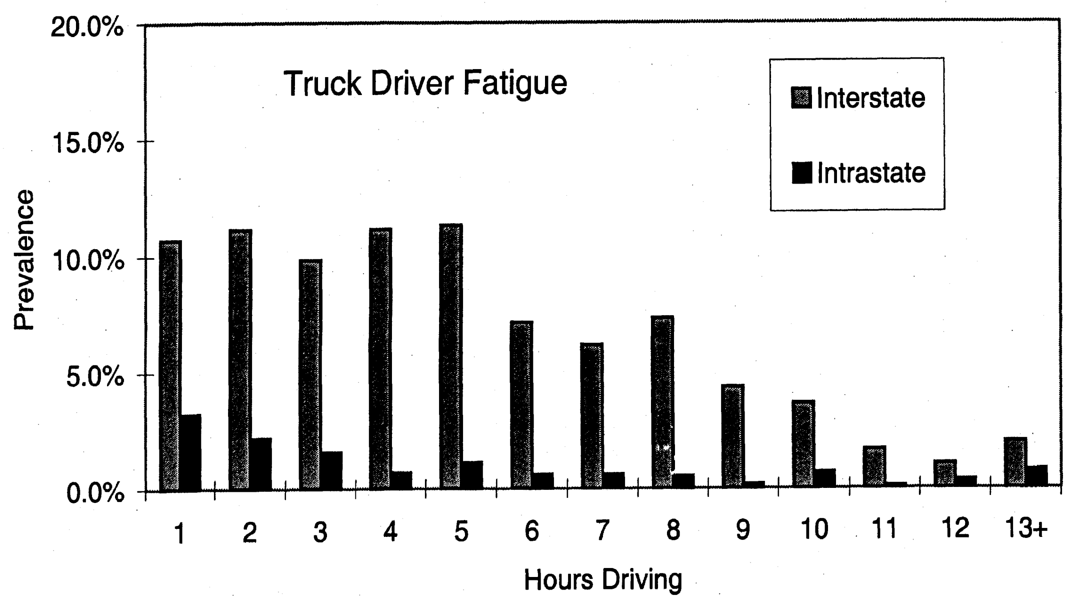

Figure 41: Hours Driving Distribution of Truck Driver Fatigue by Operating Authority Trucks Involved in Fatal Accidents 1981-1996

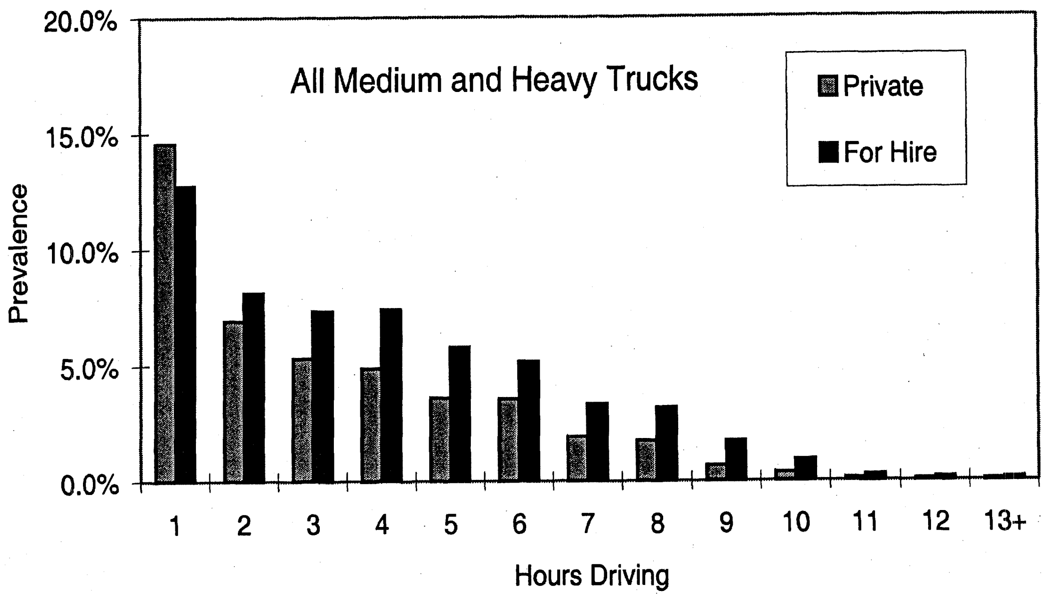

Figure 42: Hours Driving Distribution by Carrier Type Trucks Involved in Fatal Accidents 1981-1996

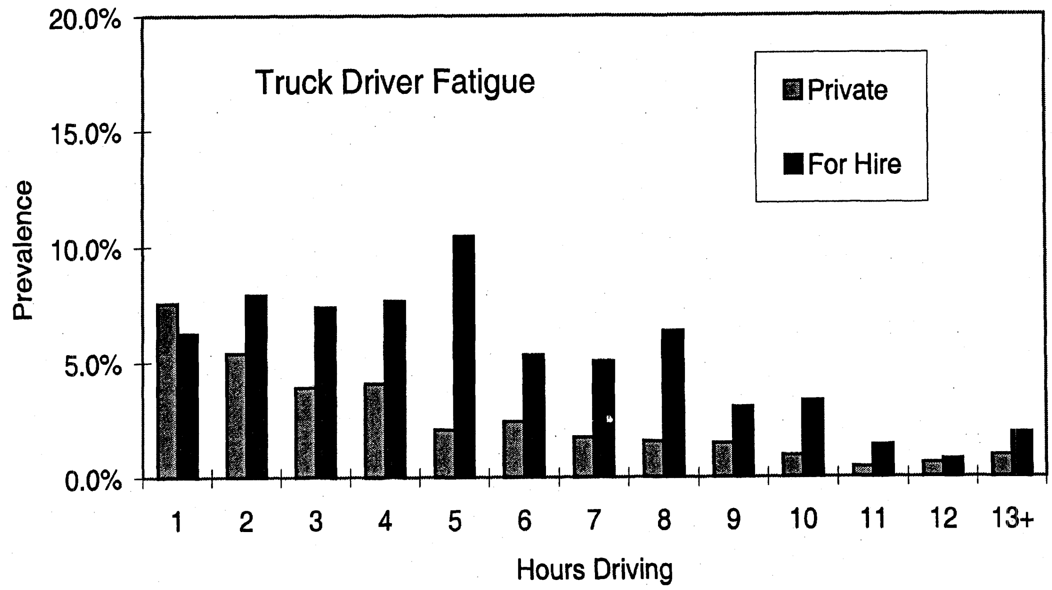

Figure 43: Hours Driving Distribution of Truck Driver Fatigue by Carrier Type Trucks Involved in Fatal Accidents 1981-1996

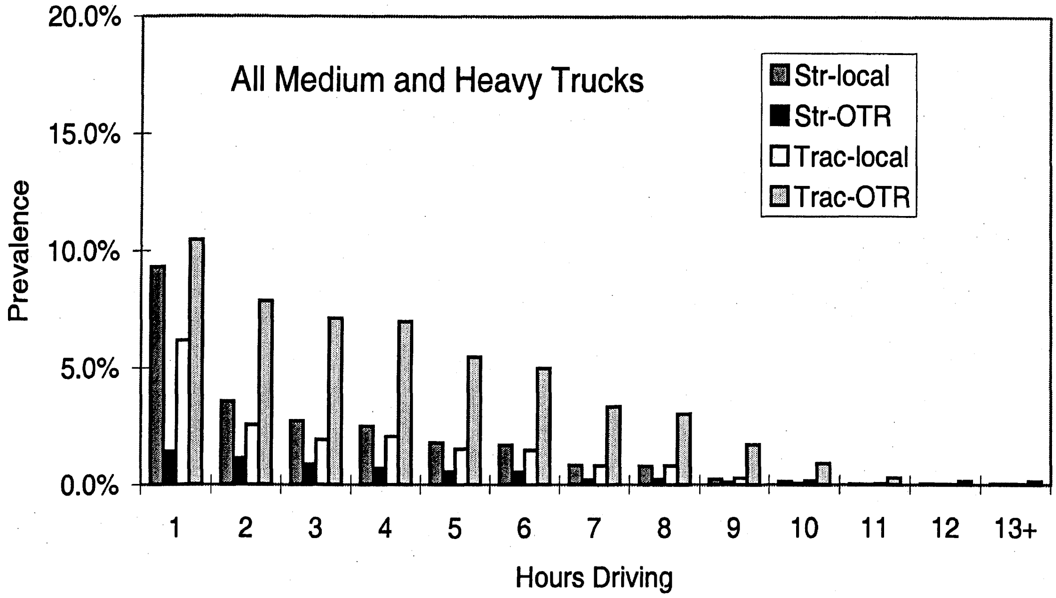

Figure 44: Hours Driving Distribution by Power Unit Type and Trip Distance Trucks Involved in Fatal Accidents 1981-1996

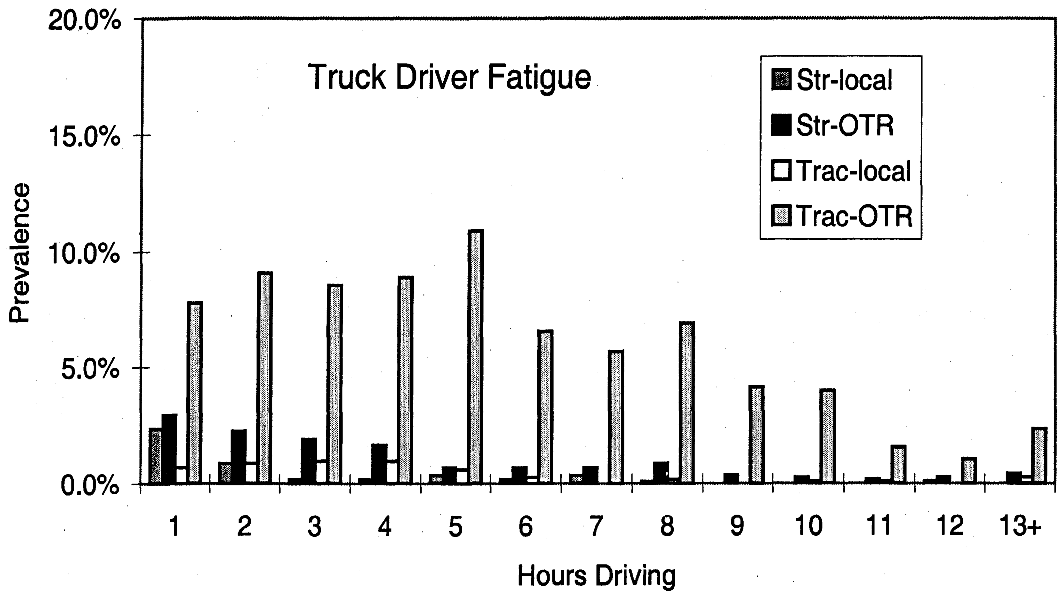

Figure 45: Hours Driving Distribution of Truck Driver Fatigue by Power Unit Type and Trip Distance, Trucks Involved in Fatal Accidents 1981-1996

1.1.3 Relative Risk Of Fatigue Based On Fatal Accident Involvement.

The relative risk of truck driver fatigue based on fatal accident involvement assesses whether fatigue is over-represented in any of the categories of the independent variables. A finding that fatigue is over- or under-represented in specific categories indicates an association between the factor level and fatigue. In the earlier example, 36.6 percent of the fatigue cases were coded over 500 miles trip distance whereas only 15.5 percent of *all* trucks involved in fatal accidents were coded trip distance over 500 miles. Thus, fatigue is over-represented in trips over 500 miles by a factor of 2.35, the ratio of these two percentages, as shown in Figure 46. The ratio takes the form of a relative risk where the denominator is based on fatal accident involvement. This calculation is convenient to use because it is scaled to produce an overall value of 1.0 for the aggregate. These percentages estimate the probability of fatigue given the truck is involved in a fatal accident. A higher relative risk, or probability of fatigue given the truck is involved in a fatal accident, indicate an association between the factors defining the subset and the risk of fatigue. Such results are only suggestive. Other factors that are associated with the subset and may or may not be in the data file may also be responsible for the association with risk that is shown. Care should be used when interpreting disaggregate relative risk values. Risk values do not sum to produce a combined risk as do counts. The risk of the combined cells must be calculated by first summing the numerators and denominators and then dividing these sums. The rate for a combination of cells will always fall between the individual cell values, but the result is a weighted average where the weighting factor is the denominator. Consequently, one cannot aggregate risk values without knowing the corresponding values for the numerators and denominators.

The results on relative risk based on fatal accident data follow in the same order of independent variables that was used in the previous section on prevalence. First the variables that are also available in 1992 TIUS (power unit type, trip distance, and carrier type), truck versus nontruck fatalities, time of day and hours driving. Combinations of these variables that were presented earlier are also included here. The sequence is listed below.

Independent Variables in 1992 TIUS

Figure 46: Trip distance (5 levels), 1994–1996
Figure 47: Trip distance (5 levels) by Power Unit Type, 1994–1996
Figure 48: Trip distance (3 levels), 1991–1996
Figure 49: Trip distance (3 levels) by Power Unit Type, 1991–1996
Figure 50: Trip distance and Power Unit type (6 levels) by Carrier Type, 1991–1996
Figure 51: Trip distance and Power Unit type (6 levels) by Truck versus Nontruck fatality, 1991–1996

Time of Day sequence

Figure 52: Time of Day, 1981–1996
Figure 53: Power Unit Type, 1981–1996
Figure 54: Trip Distance (local versus over the road), 1981–1996
Figure 55: Operating Authority (interstate versus intrastate), 1981–1996
Figure 56: Carrier Type (private versus for hire), 1981–1996

Variables in 1992 TIUS. The relative risk of truck driver fatigue based on fatal accident involvement increases with trip distance. Based on the 5-level classification, local trips are lowest, 50-100 miles and 100-200 miles are comparable, and 200-500 miles and over 500 miles are substantially higher. Given these levels, the 3-level classification maintains the most significant variation across levels of trip distance.

The interaction between trip distance and power unit type is interesting. In local trips, both straight trucks and tractors have comparable and low relative risk of fatigue. However, in any operation beyond local, straight truck drivers have substantially higher relative risks of fatigue than tractor drivers in the same trip distance category. Since straight trucks seldom take long trips, this elevated risk does not pose a problem. In fact, it may be a reflection of straight truck drivers lack of experience with fatigue on longer trips. Tractor drivers with more experience on long trips appear to manage fatigue better based on these results.

The results on trip distance and power unit type also illustrate an apparent paradox that often occurs in disaggregate risk tables. The overall relative risk for straight trucks is 0.55 and for tractors is 1.19. Aggregated across all trip distance categories, the relative risk of a fatigue involvement is more than double for tractor drivers as compared to straight truck drivers. Yet in the disaggregate data, straight trucks have equal or higher risk values in every trip distance category. This apparent contradiction is a consequence of exposure differences. The aggregate risk is not an average of the individual cell risks; it is a weighted average based on the exposure in each cell. In this case, straight trucks are used primarily on local and short trips where the risk of a fatigue involvement is lower whereas tractor are used primarily on longer trips with higher risks of fatigue. Even though tractors have a lower risk of fatigue in every cell, the aggregate risk of fatigue for tractors is more than double that for straight trucks because tractors are used more in operations with a higher risk of fatigue. In this situation, the higher risk of fatigue for tractors is clearly due to their use.

In this case, it seems that there is sufficient information to arrive at a correct interpretation of the higher fatigue risk for tractors as compared to straight trucks. In other aggregate comparisons to follow, there may be additional factors that were not considered in this analysis that contribute to the aggregate result. Consequently, the analysis has focused on disaggregate risk as much as possible given the scope of the issue and the available data.

The combination of carrier type with trip distance and power unit type shows relatively comparable relative risks of fatigue in most categories. Private carriers operating straight trucks on longer trips show somewhat higher relative risk of fatigue than do for-hire carriers in the same trip distance categories. And for-hire carriers have a somewhat higher relative risk of fatigue on trips over 200 miles by tractor drivers in comparison to private carriers. In the aggregate, for-hire carriers the relative risk of fatigue is 1.23 as compared to 0.70 for private carriers, an apparent over-involvement by a factor of 1.76. Again, this aggregate result appear to be due in part to private carriers more frequent operation on shorter trips and during daylight hours as compared to for-hire carriers.

Figure 51 show the substantial increase in relative risk of truck driver fatigue based on fatal accident involvement when the only fatalities are truck occupants. Conversely, the relative risk of truck driver fatigue is very low in multiple vehicle collisions resulting in fatality to other parties.

Time of Day. This series of results all show the circadian rhythm. The influence of time of day on the relative risk of fatigue is clearly reflected in every subset examined. Apparently none of the other factors have examined have a large enough affect on the risk of fatigue to overshadow the influence of time of day. However, there are important differences in the magnitude of the relative risk of fatigue across some of the factors examined here. Overall, the relative risk of fatigue by time of day is comparable for straight truck and tractor drivers. Straight truck drivers appear to have a slightly lower relative risk at every hour of the day. The difference is quite pronounced from 4am to 6am when tractor drivers have about one-third higher relative risk of fatigue. The overall difference between straight trucks and tractors is apparently the due to their greater use on local or short trips, as discussed earlier in this section. The larger difference in the early morning hours may be due to greater proportions of tractors on longer trips at that time of day in comparison to straight trucks. Figure 58 shows disaggregate risk by time of day for the four combinations of power unit type and trip distance. The over the road trips dominate at all times of day and straight trucks on over the road trips have particularly high fatigue risk during the night. However, the variability of the result reflects small sample sizes in many cells.

Over the road drivers in general have higher fatigue risks at all time of day. The aggregate relative risk of fatigue for drivers on local trips is 0.21 as compared to 1.54 for over the road trips, an over-involvement ratio of more than 7. The fatigue risk for drivers on over the road trips is particularly elevated from 6am to 9am in comparison to local drivers. This is also the case at 3pm, 5pm, 10pm and 11pm. The early morning difference may because most local drivers are just starting at that time, whereas some over the road drivers are approaching the end of a trip.

This same pattern shows up in the carrier type comparisons. Overall, interstate carriers are higher at every time of day, apparently because they are more likely to be on longer trips in comparison to intrastate carriers. The same is true for for-hire carriers as compared to private for the same reason. Examination of the time of day figures shows that this over-involvement is greatest in the early morning hours, the same as over the road trips in comparison to local trips discussed in the previous paragraph. The same explanation would appear to apply here. These figures also show some of the same elevations at 3-5pm as well. When the carrier type comparison is limited to interstate carriers, a similar pattern results.

For-hire interstate carriers are over-involved in fatigue-related accidents by a factor of 1.5 in comparison to private interstate carriers. This over-involvement holds at nearly all times of day, but is particularly large through most of the night and early morning hours. The prevalence data imply that interstate private carriers do much less night travel than interstate for-hire carriers. This result shows that the fatigue risk of interstate private carriers is also lower at night in comparison to interstate for-hire carriers.

Hours Driving. The relative risk of truck driver fatigue based on fatal accident involvement shows a gradual increase with hours driving. During the ninth hour the fatigue risk is nearly double and by the 12th hour the risk is higher by a factor of over 6. A pronounced increase is shown in the fifth hour. Fatigue risk drops back below 1.0 during the sixth a hour and increases with each additional hour. Aggregate risk for the second four hours is greater than the first four hours by a factor of 1.6. This pattern holds in every subset examined. Based on the caveats discussed earlier for this variable, the true risk is expected to be higher than the values shown.

The subsequent figures showing hours driving by power unit type and trip distance and carrier type all show the same pattern. Tractors, over the road trips, interstate, and for-hire carriers have higher fatigue risks in nearly every hour of driving. A closer examination reveals that these differences are somewhat larger in the 6th through 10th hours. These differences may be due to confounding variables or a cumulative fatigue effect. However, it does not show up after the 10th hour.

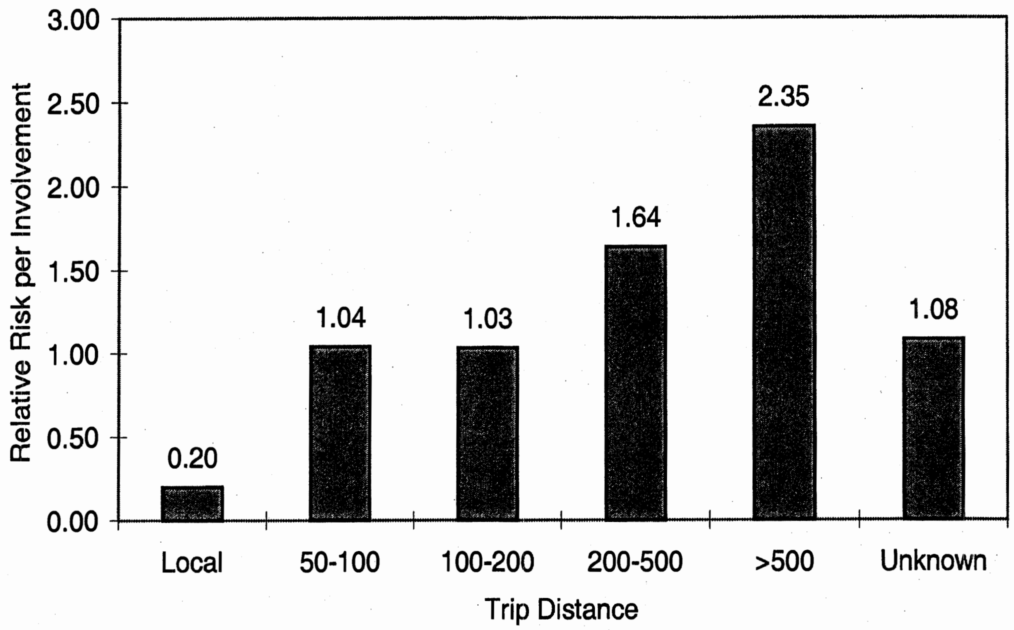

Figure 46: Relative Risk of Truck Driver Fatigue by Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996

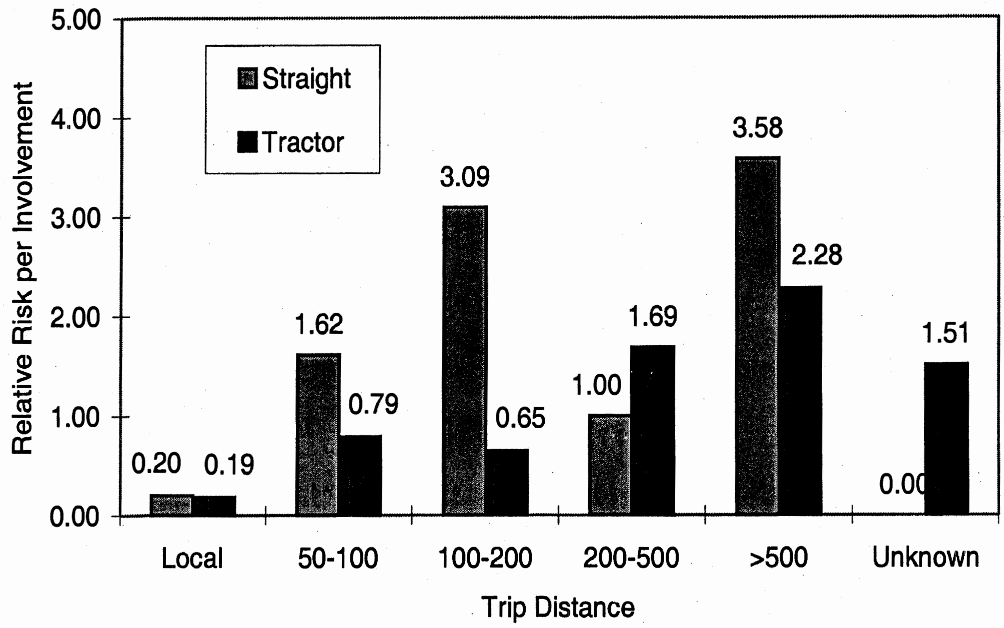

Figure 47: Relative Risk of Truck Driver Fatigue
by Power Unit Type and Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996

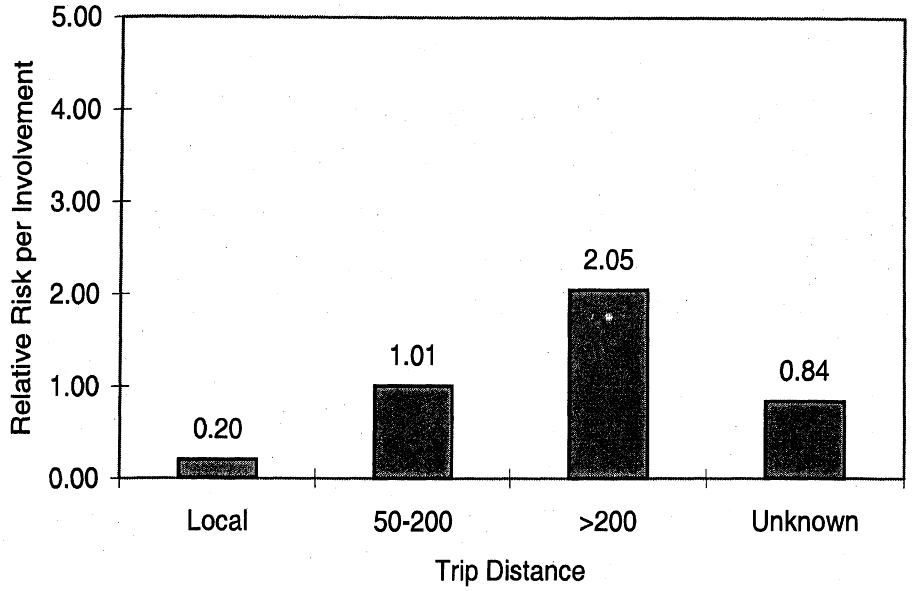

Figure 48: Relative Risk of Truck Driver Fatigue Trip Distance (3 level) Trucks Involved in Fatal Accidents 1994-1996

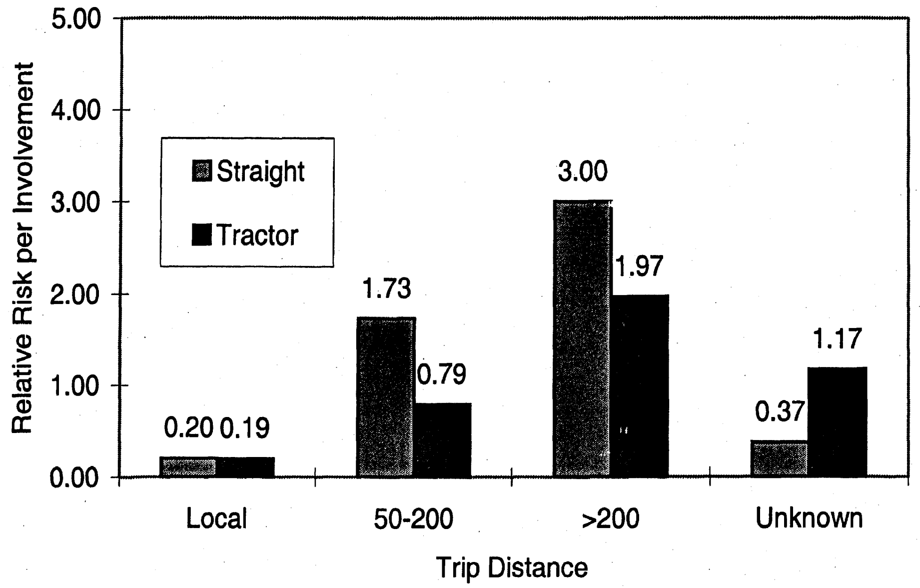

Figure 49: Relative Risk of Truck Driver Fatigue by Power Unit Type and Trip Distance (3 level) Trucks Involved in Fatal Accidents 1991-1996

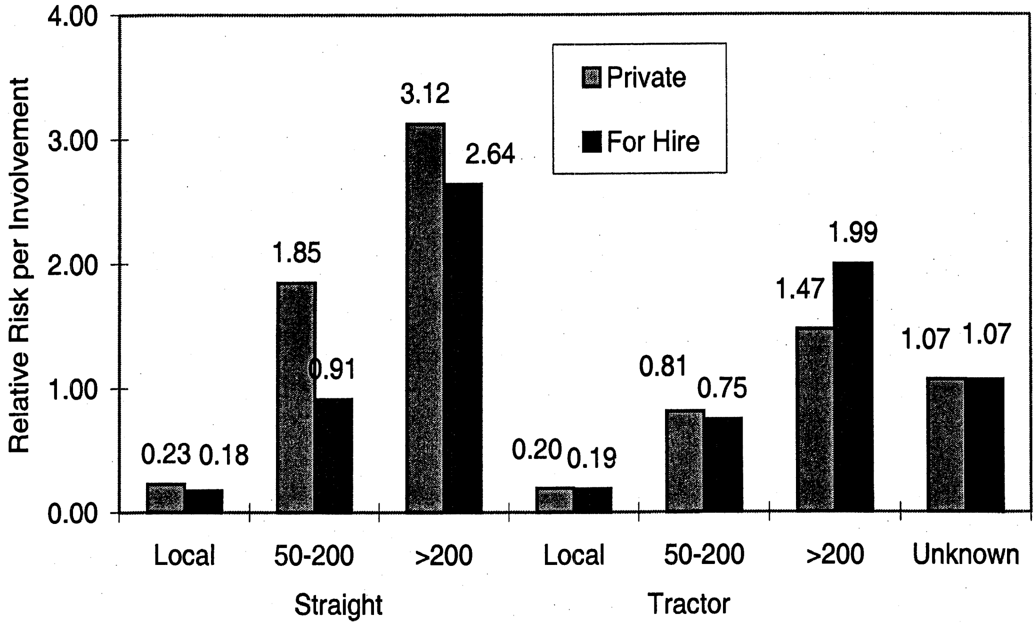

Figure 50: Relative Risk of Truck Driver Fatigue by Power Unit Type and Trip Distance (6 levels) versus Carrier Type Trucks Involved in Fatal Accidents 1991-1996

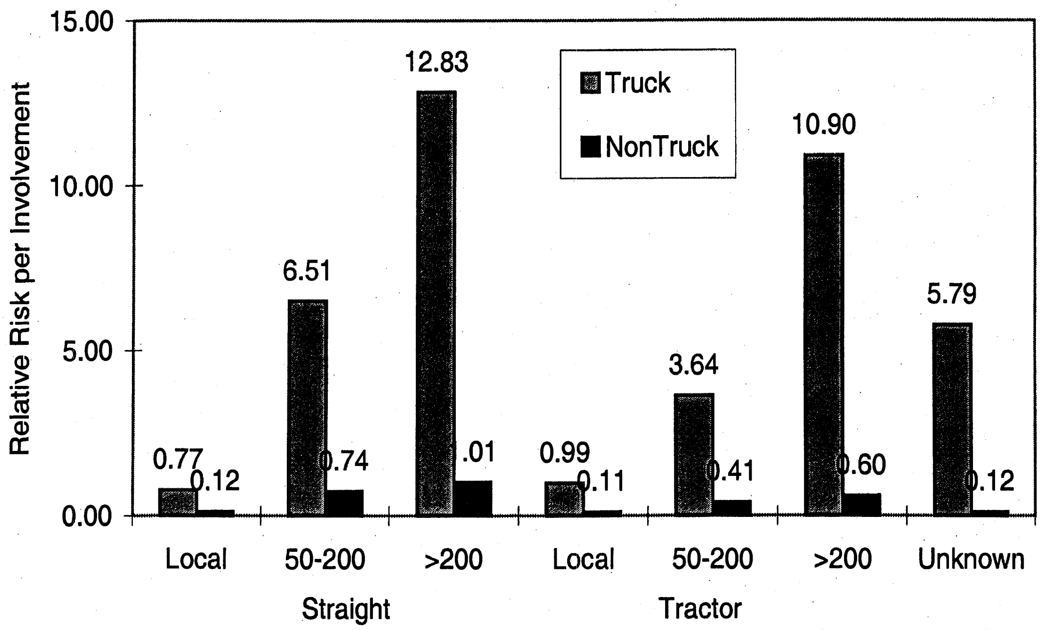

Figure 51: Truck versus Nontruck Fatalities: Relative Risk of Truck Driver Fatigue by Power Unit Type and Trip Distance (6 levels) Trucks Involved in Fatal Accidents 1991-1996

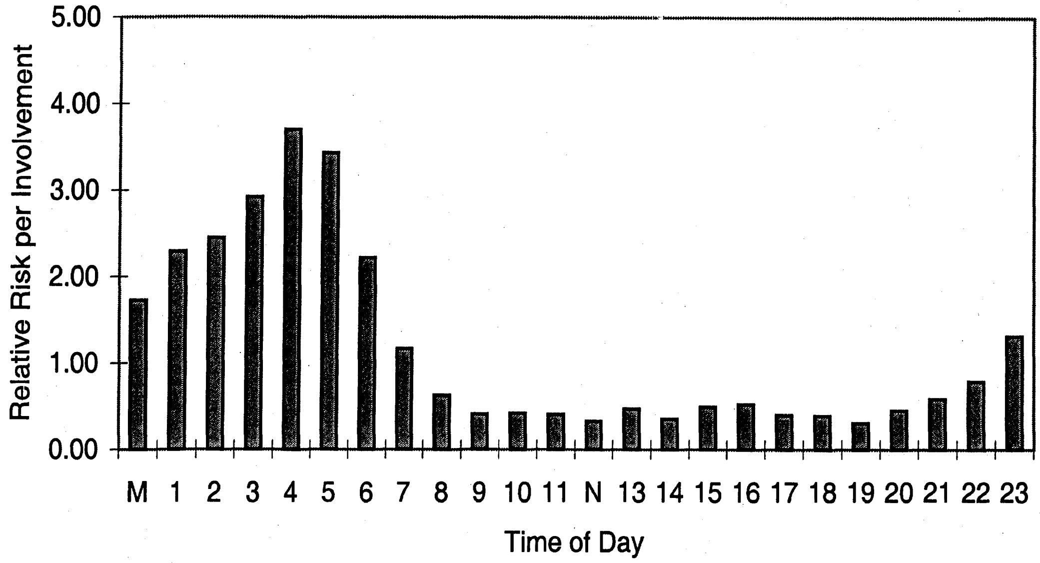

Figure 52: Relative Risk of Truck Driver Fatigue by Time of Day (TOD) Trucks Involved in Fatal Accidents 1981-1996

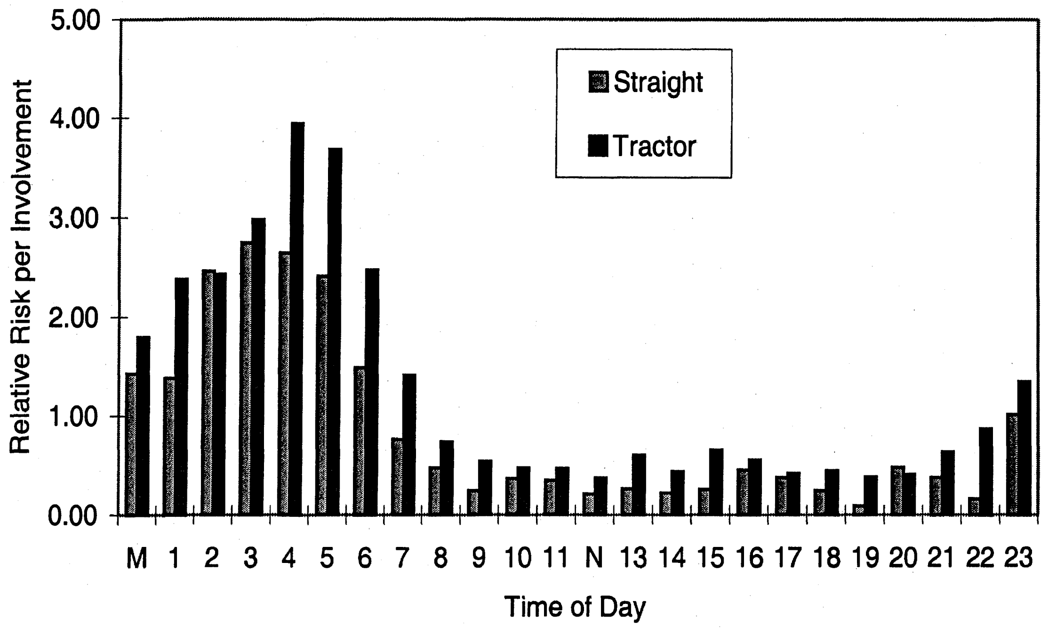

Figure 53: Relative Risk of Truck Driver Fatigue by TOD and Power Unit Type Trucks Involved in Fatal Accidents 1981-1996

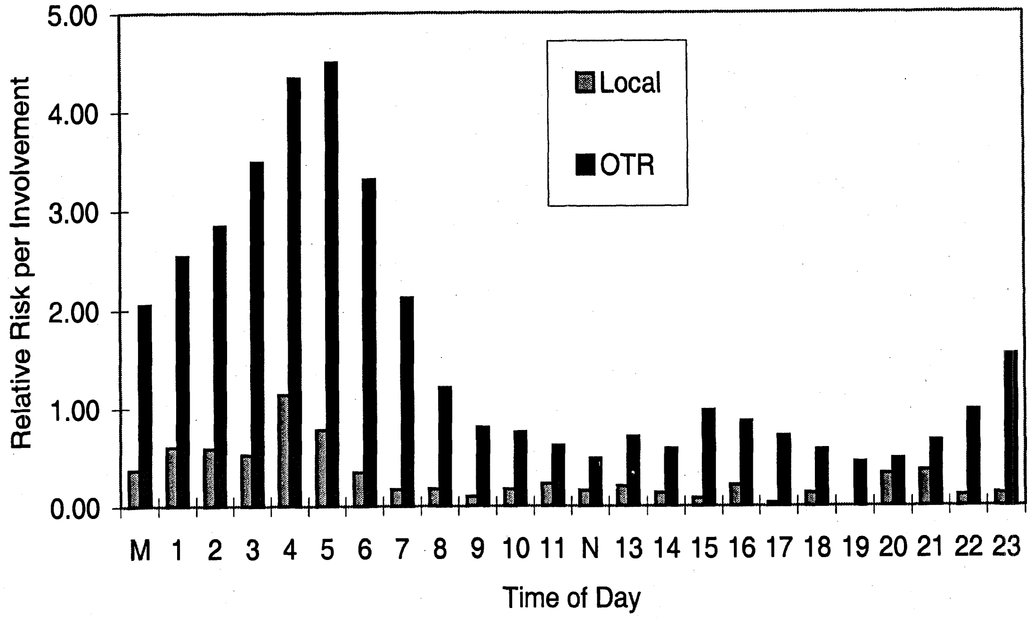

Figure 54: Relative Risk of Truck Driver Fatigue by TOD and Trip Distance Trucks Involved in Fatal Accidents 1981-1996

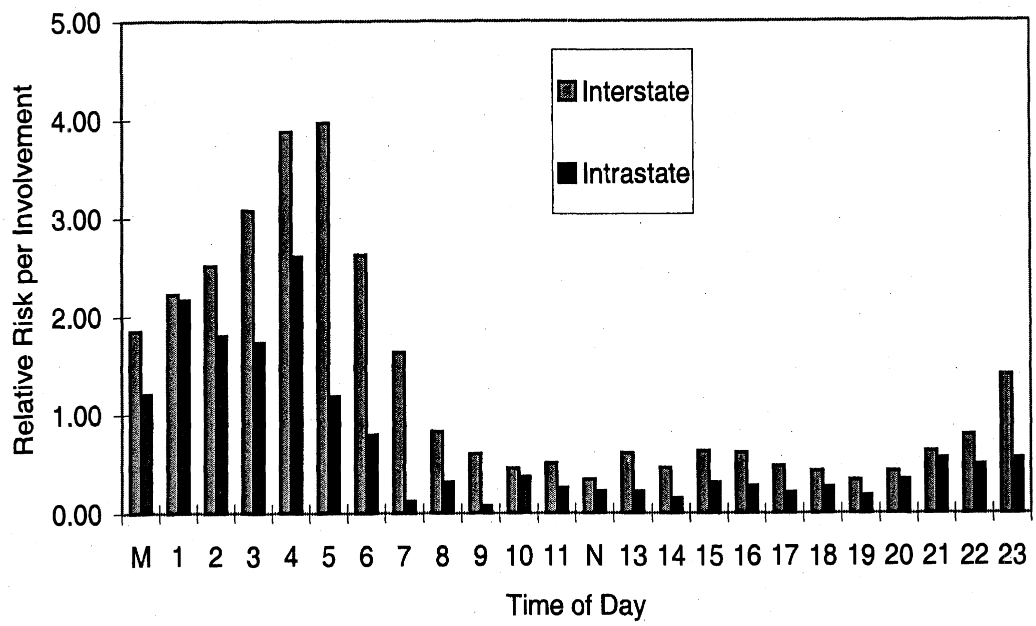

Figure 55: Relative Risk of Truck Driver Fatigue by TOD and Operating Authority Trucks Involved in Fatal Accidents 1981-1996

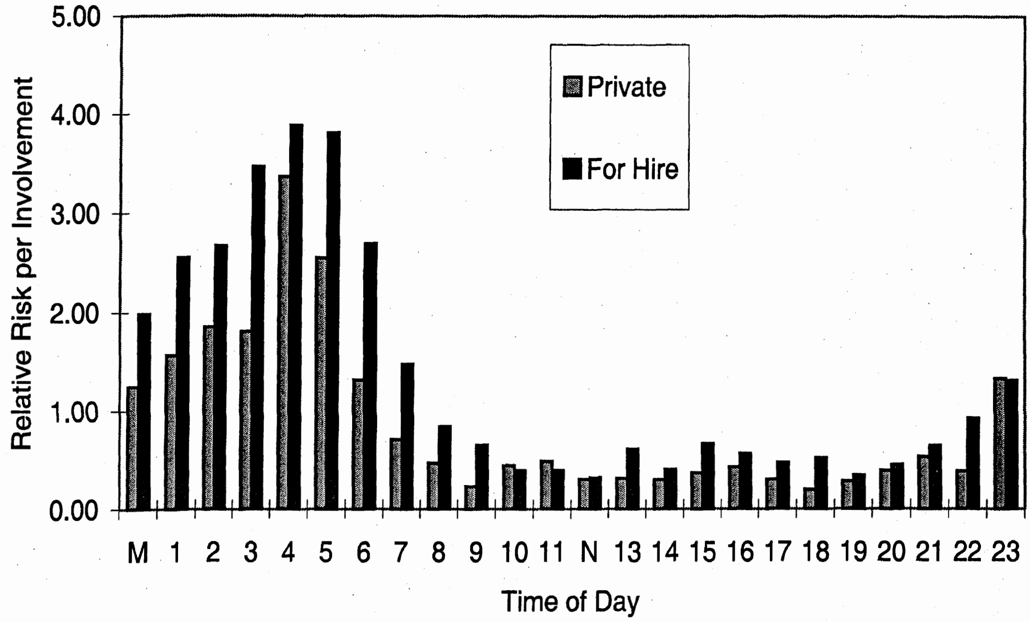

Figure 56: Relative Risk of Truck Driver Fatigue by TOD and Carrier Type Trucks Involved in Fatal Accidents 1981-1996

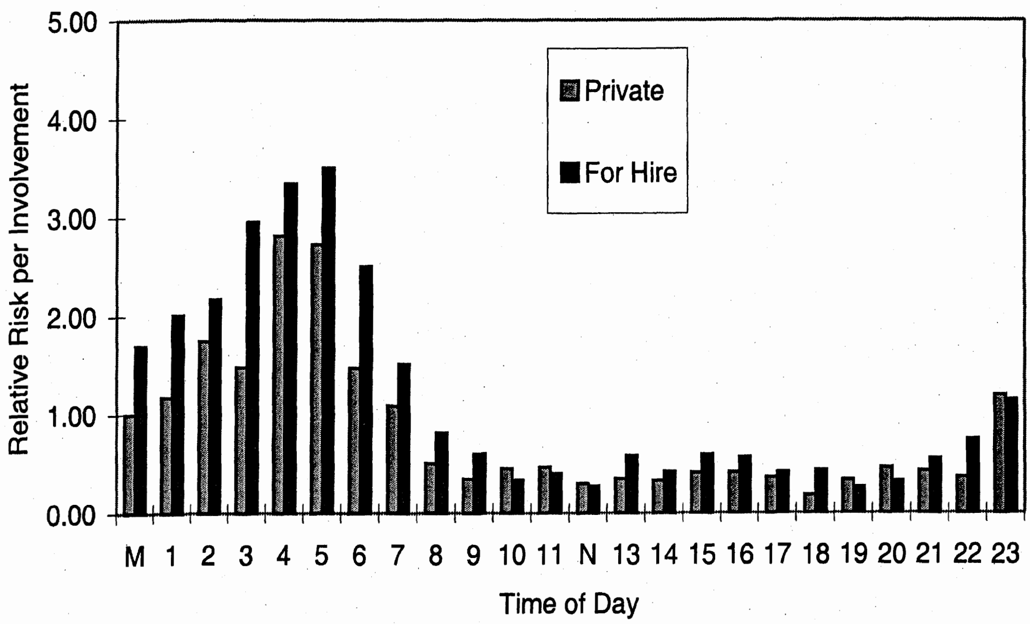

Figure 57: Relative Risk of Truck Driver Fatigue by TOD and Carrier Type—Interstate Only Trucks Involved in Fatal Accidents 1981-1996

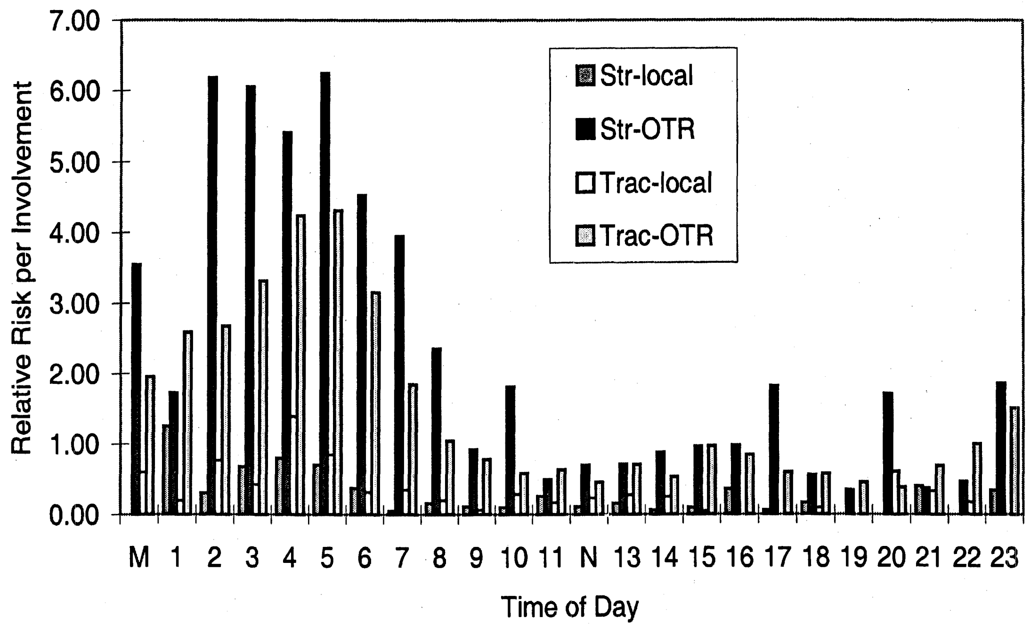

Figure 58: Relative Risk of Truck Driver Fatigue by TOD, Power Unit type and Trip Distance Trucks Involved in Fatal Accidents 1981-1996

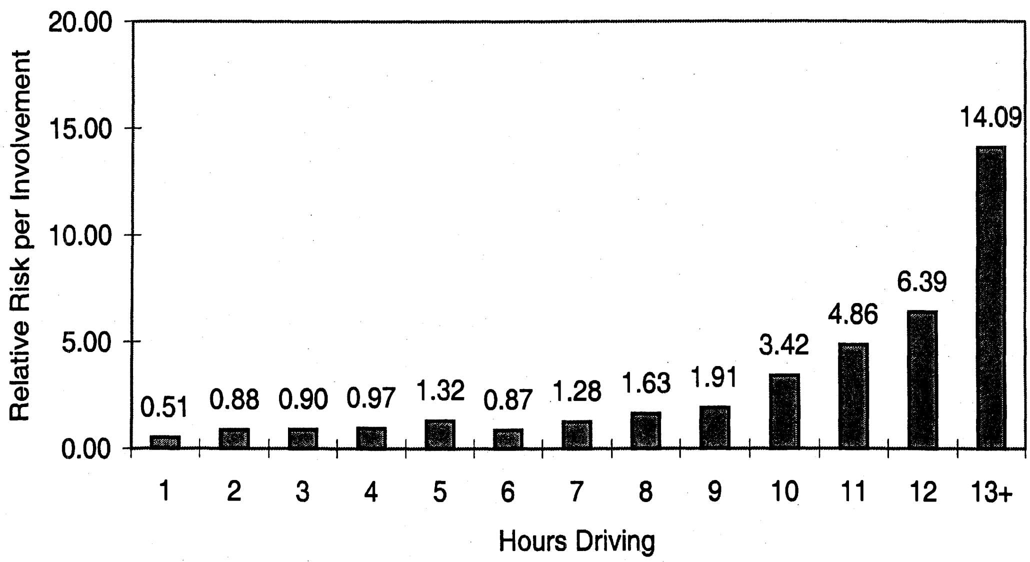

Figure 59: Relative Risk of Truck Driver Fatigue by Hours Driving Trucks Involved in Fatal Accidents 1981-1996

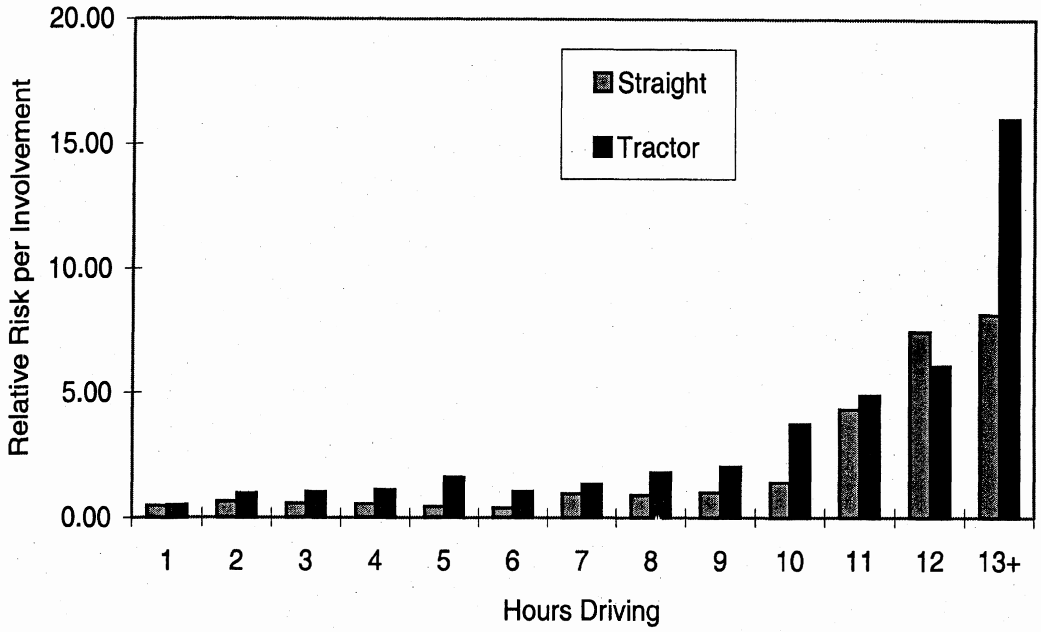

Figure 60: Relative Risk of Truck Driver Fatigue by Hours Driving and Power Unit Type Trucks Involved in Fatal Accidents 1981-1996

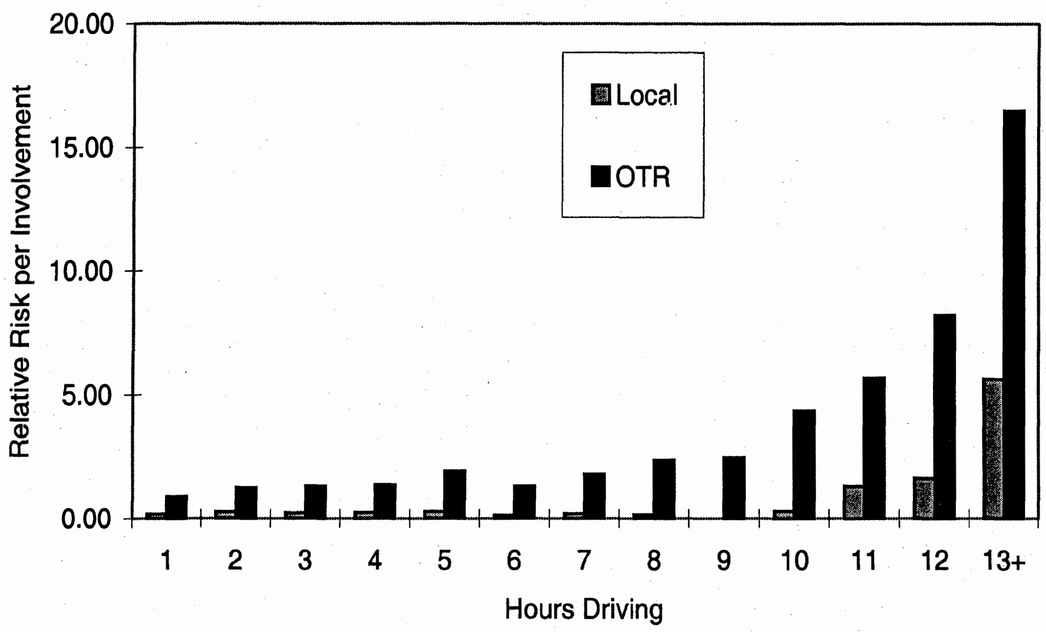

Figure 61: Relative Risk of Truck Driver Fatigue by Hours Driving and Trip Distance Trucks Involved in Fatal Accidents 1981-1996

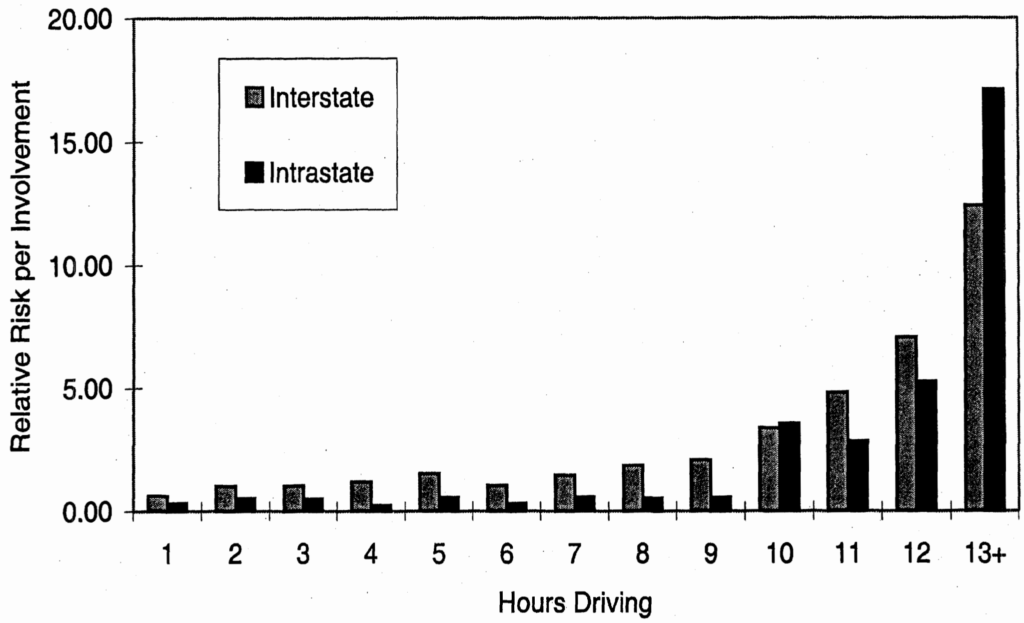

Figure 62: Relative Risk of Truck Driver Fatigue by Hours Driving and Operating Authority Trucks Involved in Fatal Accidents 1981-1996

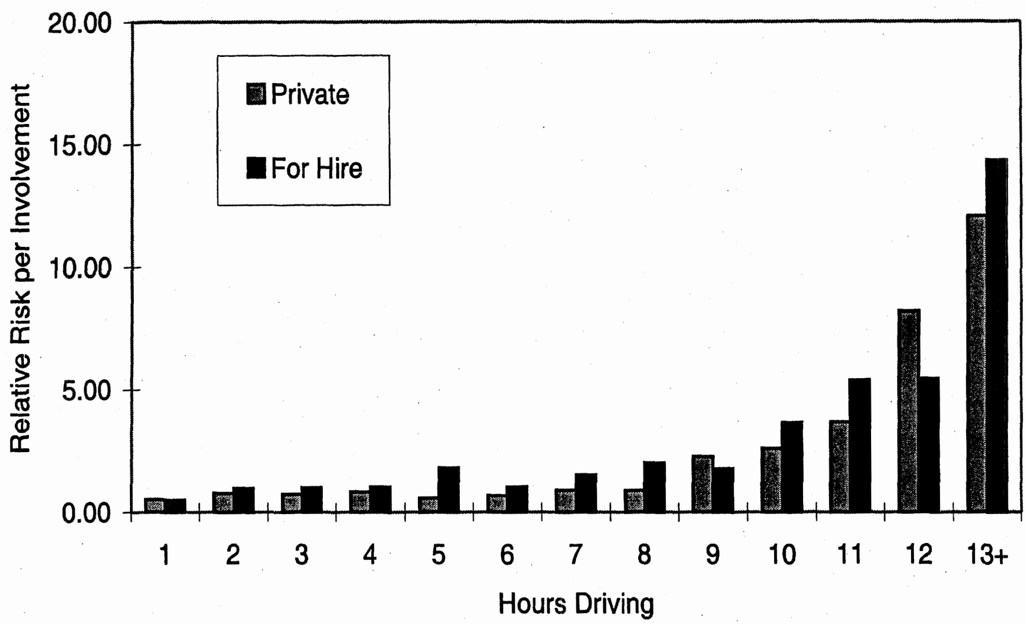

Figure 63: Relative Risk of Truck Driver Fatigue by Hours Driving and Carrier Type Trucks Involved in Fatal Accidents 1981-1996

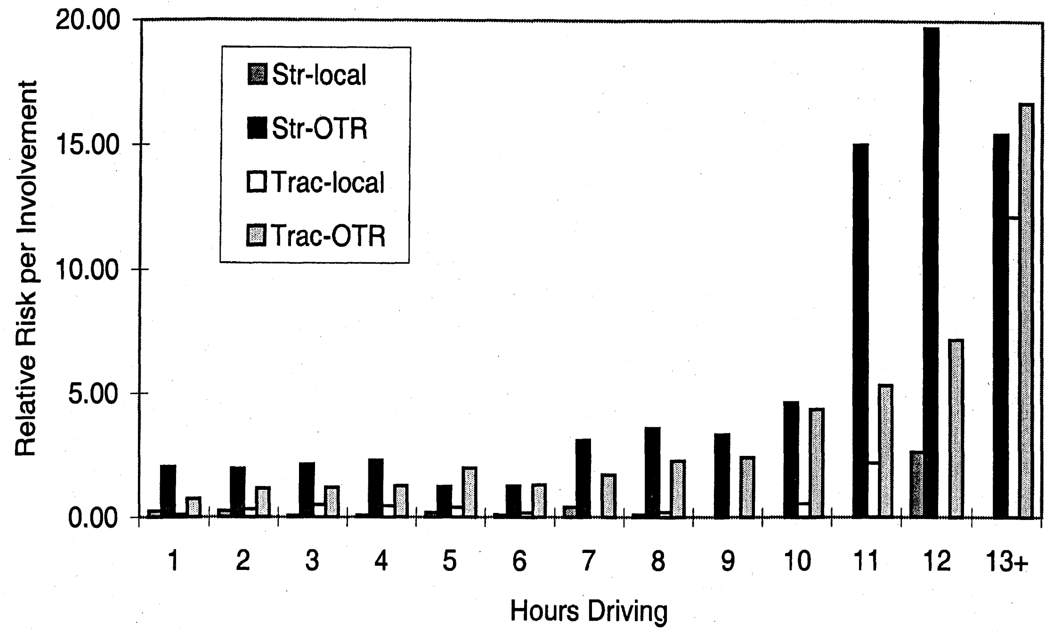

Figure 64: Relative Risk of Truck Driver Fatigue by Hours Driving, Power Unit type and Trip Distance, Trucks Involved in Fatal Accidents 1981-1996

1.1.4 Texas Data

In the FARS data, Texas reported among the highest proportion of fatigue among truck drivers. Texas is also one of the largest states, so it appears to be a good candidate to look at fatigue in non-fatal truck accidents. Fatigue is available in the Texas police-reported accident data as a code level in a driver impairment variable. The code levels available in the variable are:

1. Eyesight defective
2. Hearing defective
3. Limbs missing
4. Other physical impairment
5. Impaired by illness
6. Fatigued or asleep
7. Mentally impaired
8. Other handicap

Table 9 shows the proportion of trucks involved in accidents where driver impairment is coded "fatigue" by most severe injury in the accident. The column labeled all trucks includes all vehicles identified as a truck in the Texas data. This group may include some light trucks. There are about 770 trucks involved in fatal accidents among the cases, about 80% more than in TIFA for 1997. The column labeled "tractor-semitrailers" includes only trucks identified as such in the Texas "specific vehicle type" variable. This may be a pretty good representation. There are 294 tractor-semitrailers in fatal accidents in 1997, according to the Texas police-reported data file. In FARS, 303 tractor-semitrailers were identified in Texas.

Table 9
Percent Fatigue
1997 Texas Truck File

Severity	All "trucks"	Tractor-semitrailer
All accidents	1.50	2.45
Fatal	4.96	3.74
A&B	2.66	4.16
C injuries	0.75	1.25
PDO	1.48	2.27

Note the percentage of fatigue. From the TIFA files for 1991-1996, fatigue was 5.4% for fatal involvements in Texas. The 1997 figure from the Texas file for fatal involvements is 3.7%, as shown in the table above. This could be a reflection of the general downward trend in fatigue by year observed earlier. But it appears that the computerized Texas data may not reflect all the data captured on the police report. Checking the Texas police report, for each vehicle the officer can code up the 3 factors that in his opinion contributed to the accident and an additional 2 factors that may or may not have contributed to the accident. It appears that in the released data, some processing is going on and additional fatigue cases are lost. But the FARS analyst, looking at the police report, is able to capture more cases of fatigue (and any other driver factor). A more thorough review by the FARS analyst is one of the advantages of the FARS program

Figure 65 shows the overall distribution of driver fatigue in police-reported accidents involving a tractor-semitrailer in Texas, 1997. It shows the daily circadian rhythm that we have come to expect, even down to the slight increase in the early afternoon, though the increase may be earlier than in other data. The second series shows the overall distribution of police-reported accidents involving tractor-semitrailers. Each series in the figure sums to 100. This pattern will be repeated for the figures for fatal, A and B injury accidents, C injury accidents, and property damage only (PDO) accidents.

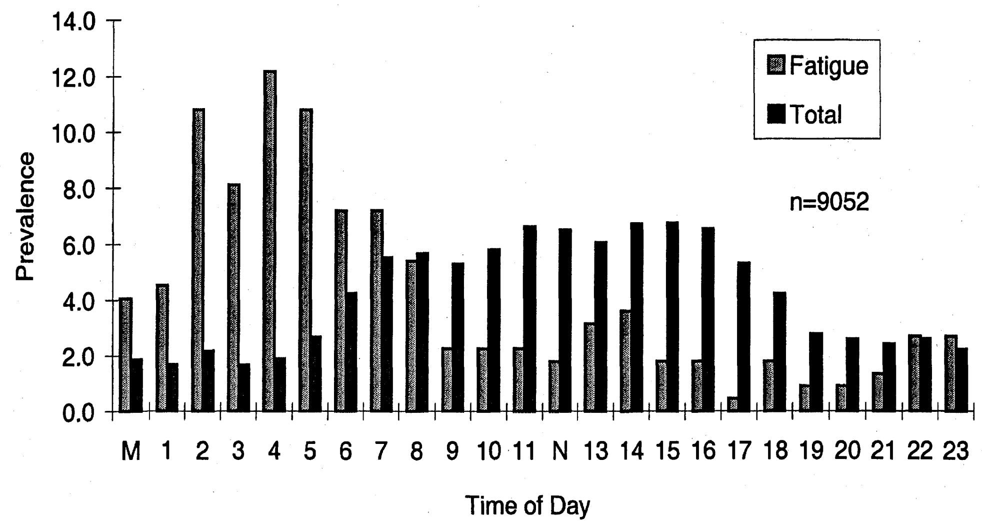

Figure 65: Distribution of Fatigue and All Tractor-Semitrailers, Texas 1997

Figure 66 is limited to only fatal involvements in Texas. Though the sample size is too small, the same pattern is evident, including the bump in the early afternoon. Only 11 fatigue cases, but the circadian rhythm can still be seen. Note how flat the distribution is of all fatal involvements.

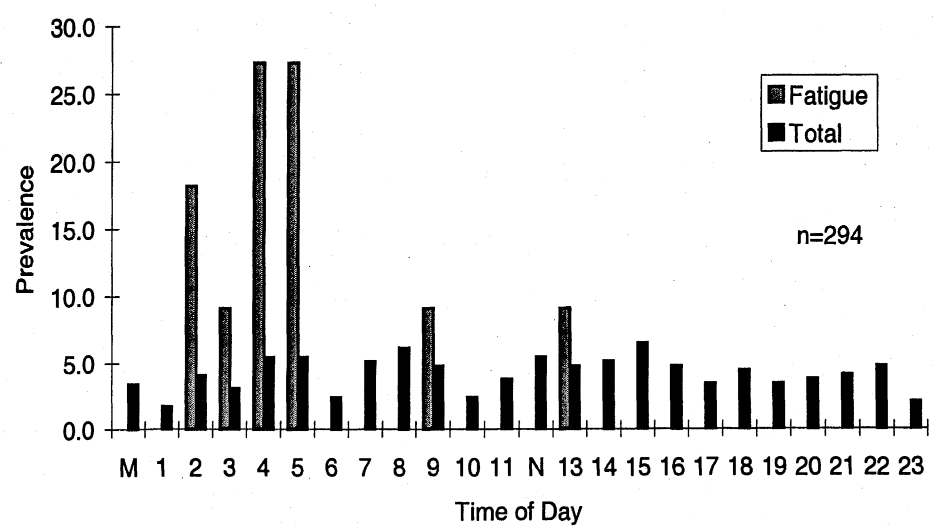

Figure 66: Distribution of Fatigue in Fatal Tractor-Semitrailer Involvements, Texas 1997

Figure 67 shows tractor-semitrailer involvements where the most severe injury in the accident was an A or B injury. This possibly arbitrary cut point was chosen to look at fairly serious accidents, not swamped with minor injuries. Again, the same pattern. And not much variation in the distribution of all A or B injury involvements by time of day.

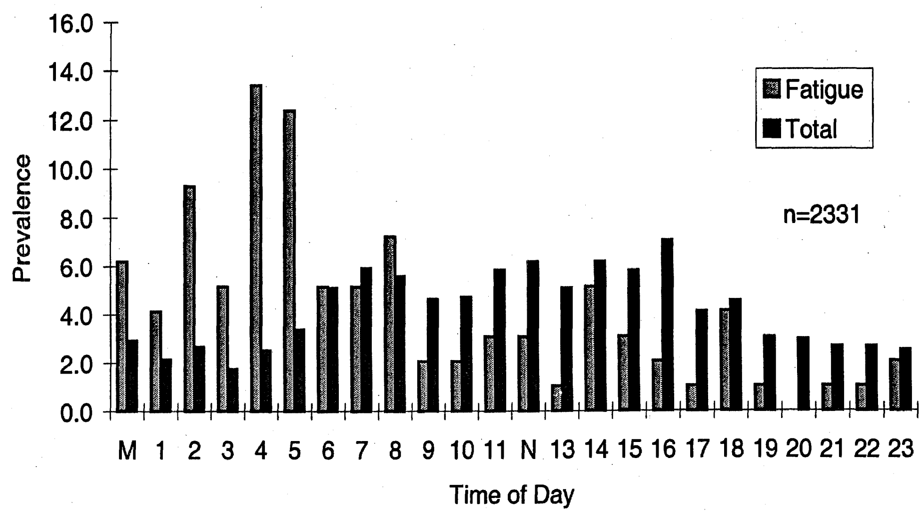

Figure 67: Distribution of A and B Injury in Tractor Semitrailer Involvements, Texas 1997

C-injury involvements shown in Figure 68 have more variation by time of day than the more serious involvements illustrated above. Fatigue-impaired involvements still follow the circadian rhythm, though with no afternoon bump. Officer may pay less attention to driver factors (and other reporting information) in minor accidents. Finally, the distribution of fatigue in non-injury (PDO) accidents is shown in Figure 69. Sample size is about the same for C injury accidents. The pattern is the same.

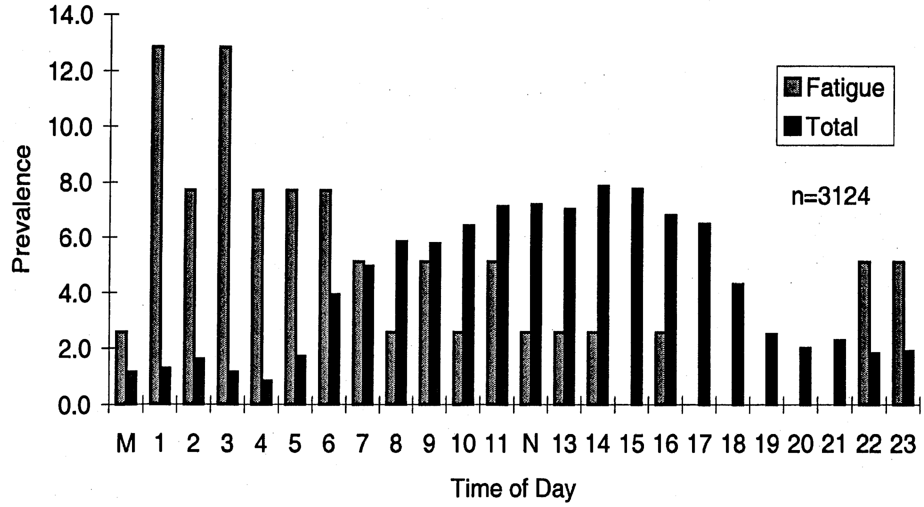

Figure 68: Distribution of Fatigue in C-Injury-Tractor Semitrailer Involvements, Texas 1997

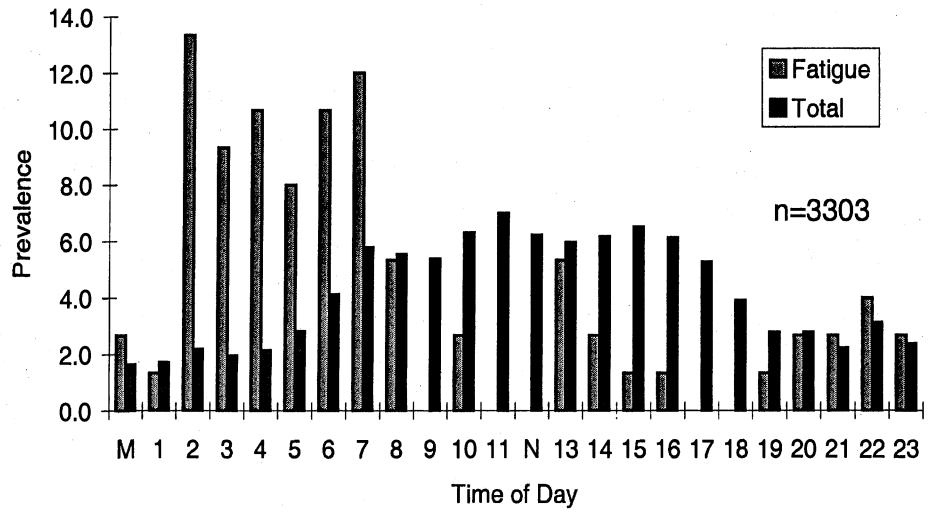

Figure 69: Distribution of Fatigue in PDO Tractor-Semitrailer Involvements, Texas 1997

The following figures show the relative risk based on accident data, for the same series of accidents by severity as the above figures: all police-reported, fatal, A&B, C, and PDO. Figure 70 is for tractor-semitrailer involvements of all accident severity. The pattern follows the circadian rhythm and the level of risk is comparable to that observed for fatal accidents.

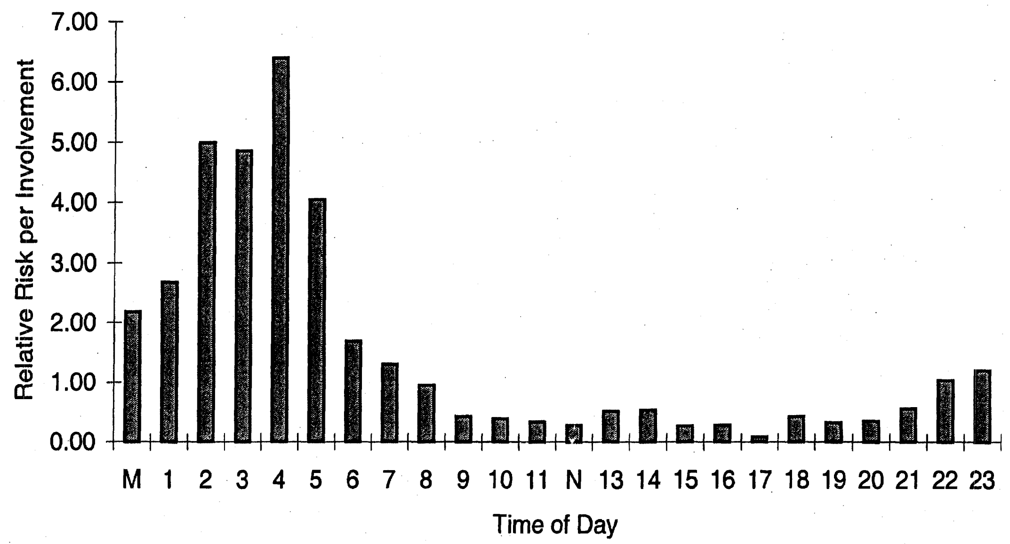

Figure 70: Relative Risk of Fatigue for All Tractor-Semitrailer Involvements, Texas1997

Fatal data shown in Figure 71are too sparse for only one year. But the magnitude of the effect and the timing are both about right.

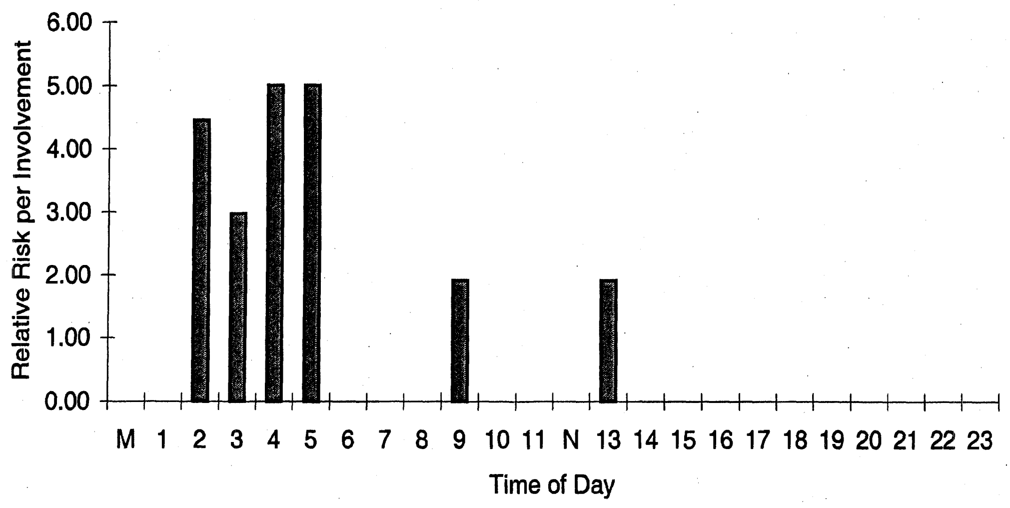

Figure 71: Relative Risk of Fatigue for Fatal Tractor-Semitrailer Involvements, Texas1997

The distribution of relative risk tractor-semitrailer involvements were the accident included either an A or B injury also looks quite reasonable, as shown in Figure 72.

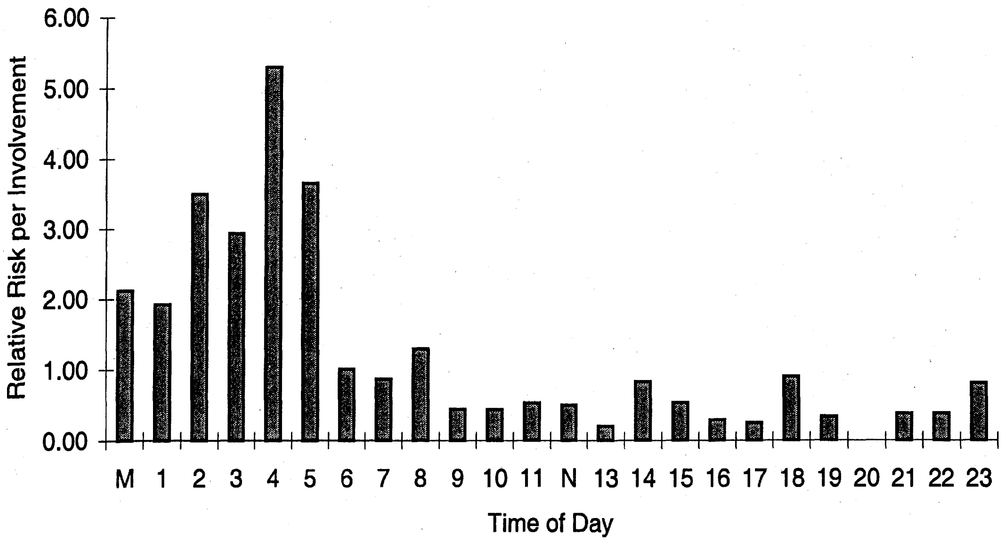

Figure 72: Relative Risk of Fatigue for A and B Injury Tractor-Semitrailer Involvements, Texas1997

Relative risk of fatigue for C-injury involvements is shown in Figure 73 and for non-injury (PDO) in Figure 74.

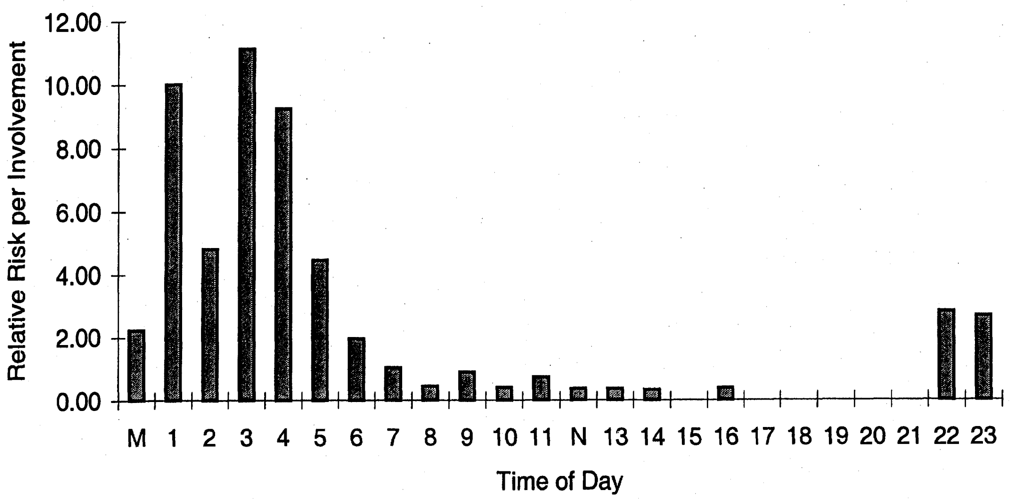

Figure 73: Relative Risk of Fatigue for C-Injury Tractor-Semitrailer Involvements, Texas1997

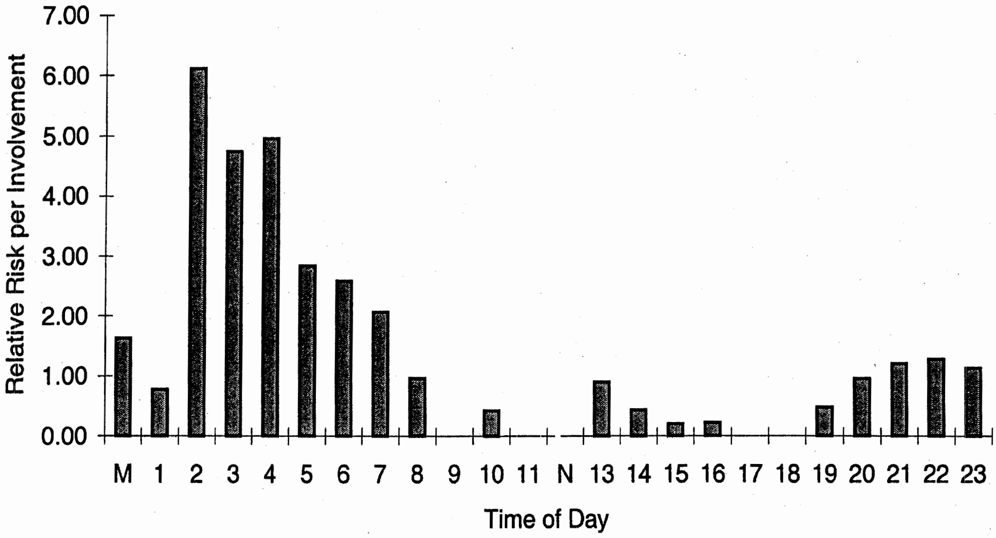

Figure 74: Relative Risk of Fatigue for Non-Injury Tractor-Semitrailer Involvements, Texas1997

Additional years of Texas data could be combined to increase sample size. However, it appears that the coding of driver factors such as fatigue may be less complete in minor accidents. One year of data confirms the circadian rhythm for all police-reported fatigue-related accidents. The pattern is evident at all injury levels and in non-injury accidents. Other factors studied here such as trip distance and carrier type are not available in the Texas data.

1.2 Population Data

The objective of this task is to refine estimates of vehicles and vehicle miles that distinguish the driver/operation subsets identified in the HOS options. The 1992 Truck Inventory and Use Survey (TIUS) is used to provide these estimates. The vehicle and vehicle miles estimates will provide denominators for the incidence of fatigue crashes from Section 1.1 to produce overall risk estimates for each driver/operation option.

UMTRI explored alternative methods of identifying trucks in the TIUS file that produced a somewhat different distribution of trucks across operation types from the July 15, 1998 FMCSA estimate. The results are discussed below. Some of the alternative approach's did not significantly change the result. Others appear to offer improvements that FMCSA might consider for subsequent estimates.

Relative risk estimates per vehicle mile traveled and per vehicle are presented in Section 1.2.3. based on the exposure estimates developed in Section 1.1.2. Variables available in both the 1992 TIUS and the 1991-1996 TIFA files are power unit type (straight truck versus tractor), trip distance (3 levels and 5 levels), and carrier type (private versus for-hire). The variable identifying interstate carriers was not usable in the 1992 TIUS. A discussion of results follows in Section 1.2.4. Relative risk of fatigue based on each exposure measure is compared to the relative risk based only on accident data and presented in Section 1.1.

1.2.1 FMCSA Estimates Of Distribution Of Trucks And Travel By Trip Distance

In the FMCSA paper, *Number of truck drivers and the distribution of travel*, (July 15, 1998) the number of trucks is estimated by trip distance and vehicle type, using the 1992 TIUS file. FMCSA subset the target population of medium and heavy trucks by including only vehicles reported to operate with an average gross vehicle weight over 10,000 pounds. Vehicles are assigned to trip distance categories by looking at variables showing the percentage of travel in trips of various distances. TIUS respondents distributed their vehicle's total travel among the following trip-distance categories: 1) less than 50 miles, 2) 50 to 100 miles, 3) 100 to 200 miles, 4) 200 to 500 miles, 5) more than 500 miles. FMCSA aggregated these trip categories to travel categories that approximate the categories used in the HOS proposed rulemaking: 1) less than 200 miles, or local; 2) 200 to 500 miles, or regional; and 3) over 500 miles, or long-haul. Vehicles are assigned to whatever category had the highest percentage of travel. In cases of ties, the vehicle was assigned to the shorter trip category. Cases with missing mileage data were assumed to have the same distribution as complete cases.

Using these methods, both the filter to identify medium and heavy trucks described above and the procedure for assigning vehicles to trip usage categories, the FMCSA produced the distribution shown in Table 10 for single unit and combination trucks:

Table 10
Distribution of Vehicles by Most Common Trip Distance, FMCSA method

operation type	single unit	combination
long-haul >500	1%	19%
regional 200-500	6%	28%
local <200	93%	53%
Total	100.0	100.0

1.2.2 UMTRI Estimates Of The Distribution Of Trucks And Travel By Trip Distance

We attempted to improve the FMCSA estimates of the distribution of vehicles and travel by two primary differences in procedure: 1) a different filter to identify medium and heavy trucks in the TIUS data, and 2) alternative means to estimate the number of vehicles in trip categories.

Medium and Heavy Truck Population in TIUS

The motivation for the different truck filter in the TIUS data is that the TIUS survey and file is not really designed to facilitate classifying trucks by gross vehicle weight rating (GVWR). The survey itself does not request that information. Using the average gross operating weight, as was done for the FMCSA paper discussed in the previous section, is plausible but subject to error. Class 3 vehicles (10,001-14,000 GVWR) typically weigh 6,000 to 7,000 pounds empty and may never operate near their rated weight, much less average their rated weight. Moreover, other variables are available in the TIUS which provide clues to the rated weight, including body type, number of axles, and number of tires.

As part of the post-survey processing of the data, the Bureau of the Census apparently adds a variable for GVWR class provided by the R.L. Polk company. The GVWR class is derived from decoding the vehicle identification number (VIN). We also used the body type, empty weight, axle count and number of tires to exclude vehicles that do not qualify as medium or heavy trucks.

To identify medium and heavy trucks in the TIUS data, we used the following filter:

- Polk VIN-derived GVWR greater than 2.
- Trucks with body type coded pickup, van, minivan, sport utility, and station wagon on a truck chassis are excluded.
- Trucks with empty weights less than 6,000 pounds, two axles, and only four tires are excluded.
- Trucks with all reported miles off-road are excluded.

This filter produces a somewhat different truck population from the filter used in the FMCSA paper. For example, about 13.4% of the vehicles in the UMTRI subset reported average gross operating weights of less than 10,000 pounds. But this is quite plausible since a class 3 vehicle can have an empty weight of 6,000 pounds or less. On the other hand, vehicles with empty weights of 6,000 pounds or less and two axles and four tires are excluded, on the grounds that such vehicles are very likely pickup trucks or some other light duty vehicle. In addition, pickups, light vans, minivans, sport utility vehicles, and station wagons built on a truck chassis are all excluded from the UMTRI subset.

Vehicle Miles Traveled

The travel estimates from the 1992 TIUS are separated into categories that correspond to the HOS options to the extent that can be supported in both the 1992 TIUS and the TIFA data files. The common variables of interest are power unit type (straight, tractor), trip distance, and carrier type (private, for-hire). Travel estimates by power unit type and trip distance are shown in Table 11. The 5-level trip distance variable in the 1992 TIUS is only available in the 1994 and later TIFA files. From 1991 to 1993, the TIFA files have the 3 level trip distance variable from the 1987 TIUS. Travel estimates are presented for both versions and each is used for the rate calculations. Figure 75 shows the distribution of vehicle miles traveled by power unit type and 5 trip distance categories.

Table 11
100 Million Vehicle Miles Traveled
All Medium and Heavy Trucks by Power Unit Type and Trip Distance
1992 Truck Inventory and Use Survey

	Trip Distance					
	Local	50-100	100-200	200-500	>500	Total
Straight	202	83	31	17	7	340
Tractor	82	103	107	162	236	690
Total	284	186	138	179	243	1,030

In the 1992 TIUS file, respondents report an annual mileage for the truck and the percent of travel in each of the 5 trip distance categories. These percentages were used to allocate each truck's annual travel to the 5 trip distance categories. The resulting figures were aggregated in each category separately for straight trucks and tractors. The percentage of total travel (straight trucks and tractors combined) are shown in Figure 75. Straight trucks accumulate 33 percent of the total travel and tractors 67 percent. This information is repeated in Figure 76 and Figure 77 for private and for-hire carriers respectively. Private carriers accumulate somewhat more travel, 53 percent, than for-hire. Most straight trucks are operated by private carriers, and straight trucks account for about 54 percent of the travel by private carriers. Conversely, straight trucks account for only about 9 percent of the travel by for-hire carriers.

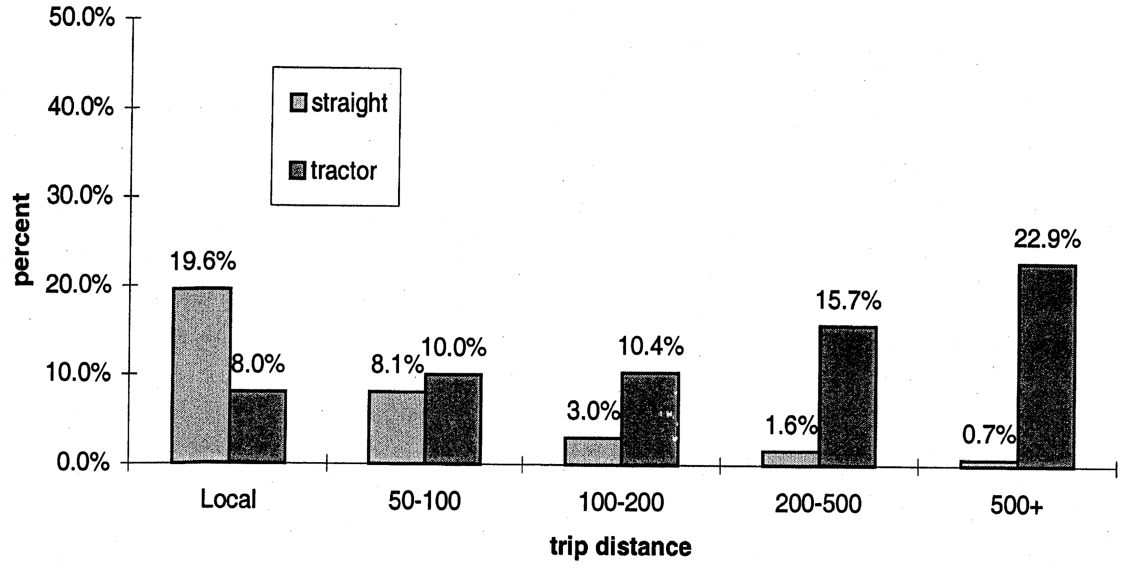

Figure 75
Distribution of Travel by Power Unit type and Trip Distance (5 levels)
1992 Truck Inventory and Use Survey

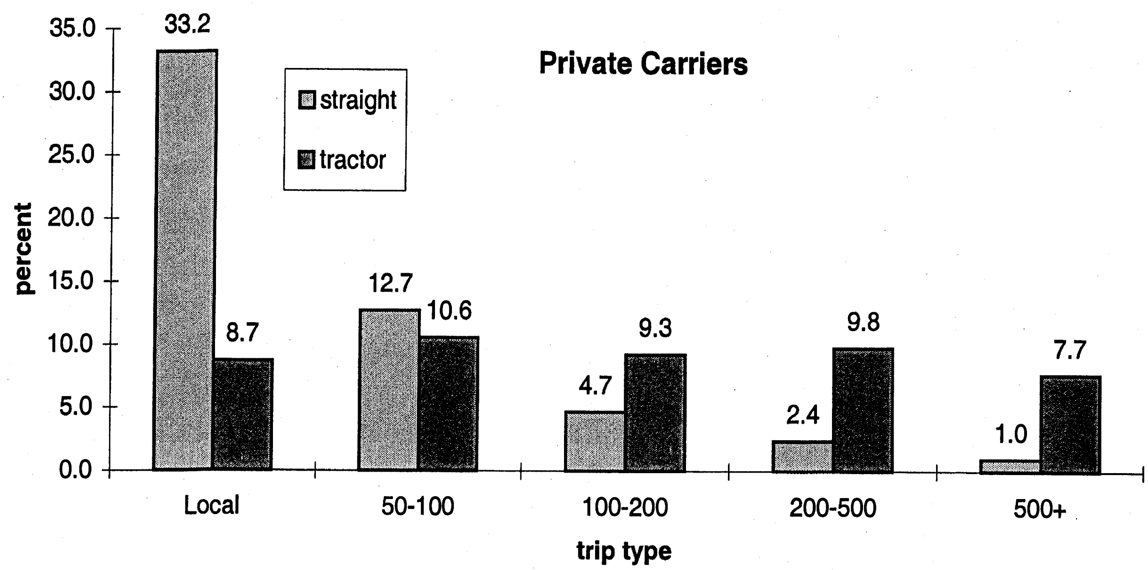

Figure 76: Private Carriers,
Distribution of Travel by Power Unit type and Trip Distance (5 levels)
1992 Truck Inventory and Use Survey

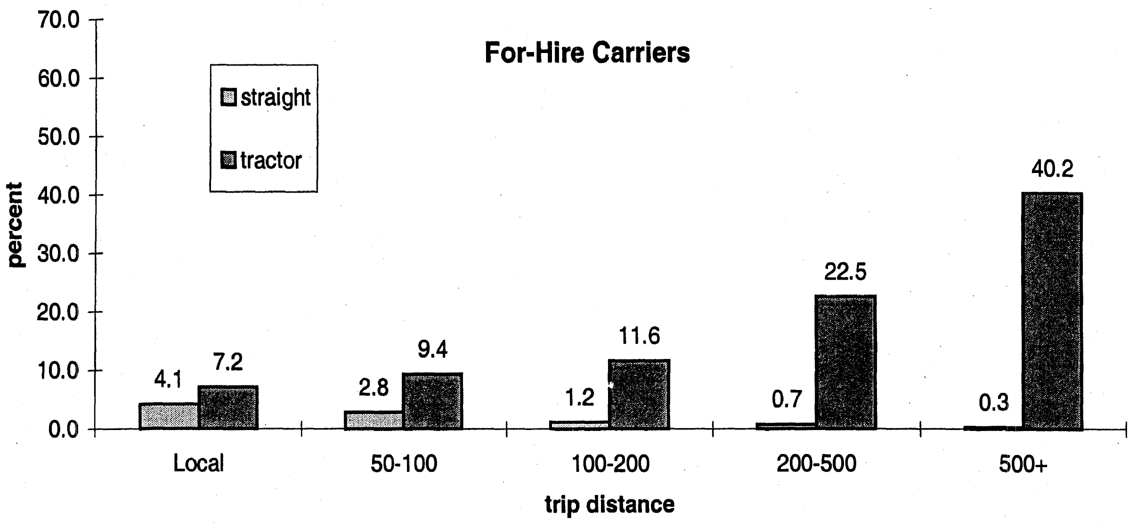

Figure 77: For Hire Carriers,
Distribution of Travel by Power Unit type and Trip Distance (5 levels)
1992 Truck Inventory and Use Survey

Similar distributions are repeated in Figure 78 and Figure 79 after combining to 3 trip distance categories. Figure 79 combines all three variables and shows overall percentages of travel.

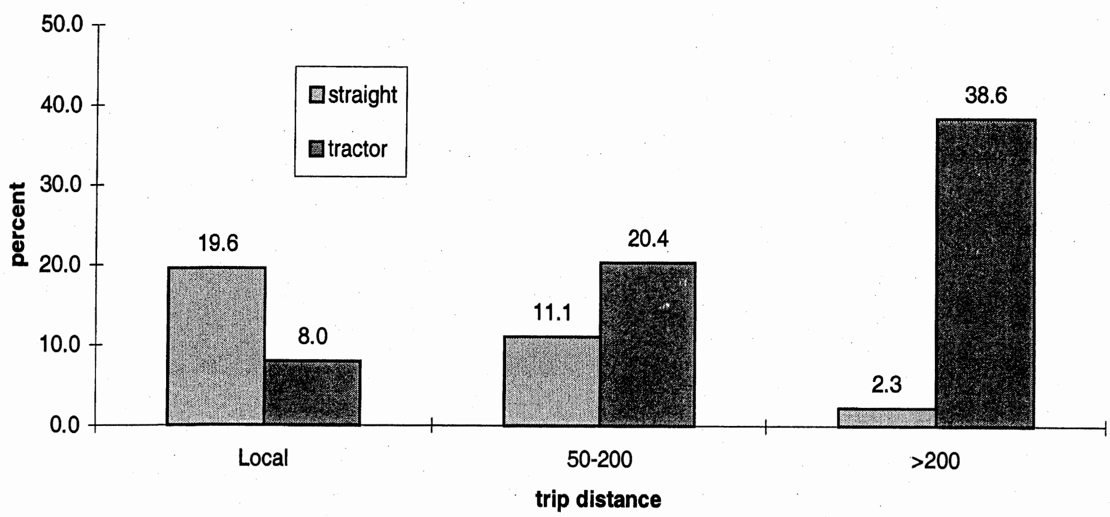

Figure 78
Distribution of Travel by Power Unit type and Trip Distance (3 levels)
1992 Truck Inventory and Use Survey

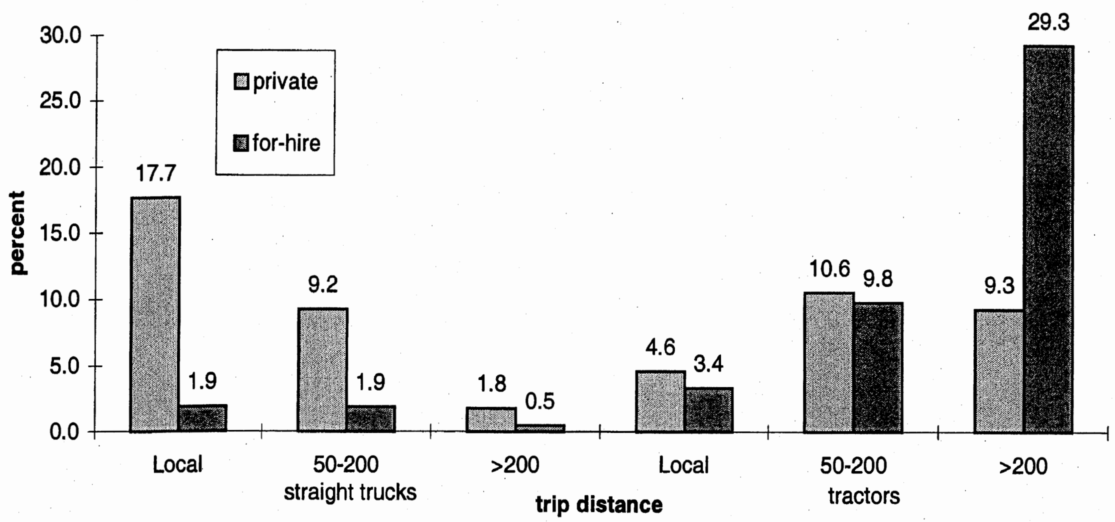

Figure 79
Distribution of Travel by Power Unit type, Trip Distance, and Carrier Type
1992 Truck Inventory and Use Survey

Exploration of Methods to Assign Vehicles to Trip Categories

Table 12 shows the result of using the FMCSA method of assigning vehicles on a file that used the truck filter developed by UMTRI. For this table, we developed an algorithm that follows the procedure described in the FMCSA paper, but ran it on our own truck subset. Trucks reported by respondents to be used primarily as straight trucks only were classified as "single unit." Trucks reported by respondents to be used primarily as a straight truck with a trailer or a tractor with a trailer were classified as "combination." As reported above, respondents distributed the travel of their vehicles across five different trip length categories. Trips reported to be within 50 miles of base, 50 to 100 miles, and 100 to 200 miles were aggregated as "local." Trips reported in the 200 to 500 miles category were considered to be "regional." Trips reported over 500 miles were classed as "long haul."

As in Table 10, this table shows the distribution of vehicles assigned to the operations category with the preponderance of travel. The distribution is quite different from Table 10, however. For long-haul, the proportions are comparable, but the regional category is significantly less than Table 10and the local category is significantly more. For combination vehicles, the population produced by the UMTRI filter has about 14.1% in the regional category, compared with 28% of the FMCSA subset. And over two-thirds of combination vehicles are local, compared with 53% of the FMCSA-subset combination vehicles.

Table 12
Distribution of Vehicles by Most Common Trip Distance,
FMCSA Method, UMTRI TIUS subset

operation type	single unit	combination
long-haul >500	0.6	18.1
regional 200-500	1.0	14.1
local <200	98.4	67.9
Total	100.0	100.0

The FMCSA paper assigned vehicles as local, regional, or long-haul by the trip type reported with the greatest proportion of travel. This is a reasonable method of assignment. However, it does not take into account the fact that particular trucks (and drivers) may take trips of differing lengths over the course of a year. In the extreme, if a respondent filled out a survey so that 33% of miles were assigned to the local category, 33% to the regional and 34% to long-haul, by the FMCSA method, the truck would be treated as if all its travel were long-haul.

Two alternatives were considered. The first was simply to assign vehicles in *proportion* to the travel in a particular operations category. In other words, if 30% of the single unit travel is in the regional category, then assume that 30% of the trucks fall into that operations type. In this method, particular trucks are not assigned to an operations category, but instead "virtual" trucks are assigned to the different operations categories. The result is shown in Table 13.

Table 13
Distribution of Vehicles by Average Travel

Operation type	Single Unit	Combination
Long-Haul >500	1.5	32.9
Regional 200-500	4.3	22.9
Local <200	94.2	44.3
Total	100.0	100.0

The weakness of this method, however, is apparent: It assumes that the average travel of a truck used in each operation type is the same; for example, that a combination truck used exclusively for long-haul operations accumulates just as many miles as one used in local service. It is equivalent to dividing the total travel for a cell by the average travel for a truck type. But this is clearly wrong. Long-haul trucks typically cover many more miles annually than local service trucks, even when "local service" is defined to include trips of up to 200 miles.

Accordingly, a second alternative was developed. The alternative is essentially a refinement of the first. However, instead of using average travel for a truck type (single unit or combination) across all operations categories, the mean travel for a truck primarily used in each operations category is determined and then the total number of such trucks implied by the total travel for the cell is calculated. This is accomplished by dividing the total travel in each cell by the mean travel for a typical truck used for each operations type.

To determine an average travel for a typical vehicle, we looked at distributions of travel by truck type across the different operations types. The purpose was to understand the variation among trucks in their distribution of travel across operations types. If there was a large group of trucks in each operations category that was used exclusively in that category, those trucks would be good candidates to calculate a average or mean travel for a truck used in each category. In fact, however, the distributions showed that most trucks are used overwhelmingly in local operations. To get reasonable estimates for the regional and long-haul categories, it was necessary to expand the range of travel to at least 75% of travel.

About 70% of straight trucks and 44% of combination trucks have all of their travel in the local (<200) trip category. For operations of 500+ miles (the long-haul category), 0.13% of straight trucks accumulate 100% of their travel in that category, and 8.3% of combinations. The regional (200-500) category really falls between two stools. Ninety-four percent of straight trucks and 66% of tractors have less than 5% of their travel in that category. One-half a percent of straight trucks and 4.9% of tractors have all travel in the regional category. Expanding the range to 75-100% of travel in the regional category, the proportions are 0.7% for straight trucks and 8.8% for tractors. For the long-distance category, the equivalent proportions are 0.4% of straight trucks and about 13% of combination trucks. Almost three-fourths of combinations accumulate less than 5% of their travel on trips over 500 miles. Over 97% of straight trucks accumulate less than 5% of their travel on trips over 500 miles.

Table 14 shows the calculated mean travel for single unit and combination vehicles by operations type. The column head "N" shows the unweighted sample sizes on which mean travel estimates are based. Mean travel is weighted. Note the relatively small number of cases for the long-haul and regional categories of single unit trucks. The mean annual travel for combination trucks appears to be plausible, with combinations operated in the long-haul segment averaging over 100,000 miles per year, while local combinations average only about 35,000 miles. It is also likely that the local single unit estimate is solid, given the large number of cases. However, for single unit trucks, mean travel for regional and long-haul operations appear to be reversed.

Table 14
Mean Travel by Truck Type For Vehicles in Which 75 Percent Or More Of Their Total Travel is the Particular Trip Distance Category

	Single Unit		Combination	
Operation Type	N	Mean travel	N	Mean travel
Long-Haul >500	224	23,079.67	7,198	101,419.66
Regional 200-500	238	37,396.90	4,117	79,153.32
Local <200	25,486	13,045.80	24,348	34,685.99

Table 15 shows the resulting distribution of trucks, based on the procedure outlined above. The distribution is determined by dividing the total travel in a particular operations category by the mean travel of units that accumulate 75% or more of their travel in that category:

Table 15
Distribution of Vehicles by Typical Average Travel For a Unit Primarily Used in Each Operations Type

Operations Type	Single Unit	Combination
Long-Haul >500	0.9	17.2
Regional 200-500	1.5	15.3
Local <200	97.6	67.5
Total	100.0	100.0

Overall, the distribution of trucks produced by this procedure is quite similar to the distribution produced by the simpler FMCSA method of assigning each vehicle to the operations category with the greatest travel as displayed in table 2. The largest relative differences are in the single unit long-haul and regional operations cells, but both are around 1% for both methods. The distributions of combination vehicles are very close, with 17%-18% of combination vehicles in long-haul service and 14%-15% in regional service.

The differences in results between the more elaborate method of assigning vehicles developed by UMTRI and the simpler, more straightforward method used in the FMCSA paper are likely not significant. Though there might be theoretical reasons for preferring the UMTRI method, since the results do not appear to be appreciably different from the FMCSA procedure, simplicity favors the latter. The major difference between the estimates of vehicles arrived at here and those in the FMCSA paper summarized in Table 10 above are the result of the different and more restricted truck population subset from the TIUS file.

In the FMCSA paper, the ultimate aim of estimating the distribution of trucks across operations types is to estimate the number of drivers across operations types. Trucks are used as a proxy for drivers. The full range of operations types identified in the HOS proposal includes "labor primarily other than driving" (LPOD) and split shift. No estimate of split shift drivers is possible from TIUS; in any case, split shift drivers are primarily either school or transit bus drivers, who are not covered by the HOS regulations.

The TIUS file does not directly identify trucks that are used primarily for non-driving purposes. However, the file does identify the industry in which the vehicle is used. FMCSA developed a rule of assigning homebase vehicles to LPOD operations, based on the type of industry in which the vehicle is used. The rule is given in table 2 of the FMCSA paper and will not be repeated here. Applying the FMCSA rule to the population of trucks identified by the UMTRI produces the distribution of trucks shown in Table 16 below. This distribution is very similar to the FMCSA distribution, except UMTRI estimates about 7% more homebase trucks and about 7.2% fewer regional vehicles.

Table 16
Percent of Trucks by Operations Type

Operations Type	Percent
LPOD	18.6
Homebase	69.1
Regional	5.6
Longhaul	6.7
Total	100.0

Finally, we can estimate the number of drivers by the operations types. FMCSA estimated a total of $6.43*10^6$ truck drivers subject to the HOS regulations. This estimate appears to be based on reasonable assumptions and the best available data, so we will adopt that number here. Using the distribution of trucks across operations types in Table 16, Table 17 shows the resulting distribution of drivers by type of truck operations. Again, we estimate somewhat more homebase truck drivers than FMCSA, 4.4 million to about 3 million in the FMCSA paper. The difference is almost entirely accounted for by the regional category, where we have about 360,000 drivers, and the FMCSA paper estimates 823,000.

Table 17
Number of Drivers by Operations Type

operations type	number
LPOD	1,197,176
Homebase	4,447,573
Regional	360,440
Longhaul	431,241
Total	6,436,430

Number of Vehicles

The distributions of registered trucks from the 1992 TIUS file are much different than the distributions of vehicle miles traveled. The difference arises from the large differences in annual travel for straight trucks as compared to tractors. Consequently, the distribution of the vehicle population is substantially different from the distribution of travel. The resulting estimates of the number of registered medium and heavy trucks is shown in Table 18.

Table 18
Medium and Heavy Truck Registrations by Power Unit Type and Trip Distance
1992 Truck Inventory and Use Survey

	Trip Distance					
	Local	50-100	100-200	200-500	>500	Total
Straight	2,215,105	356,653	98,398	40,772	22,768	2,733,696
Tractor	341,666	206,752	148,517	201,297	243,334	1,141,566
Total	2,556,771	563,405	246,915	242,069	266,102	3,875,262

Three figures showing the distribution of registered trucks are given for comparison to the earlier distributions of travel. These differences will directly carry over to the accident rates presented in the next section. Figure 80 shows the distribution of trucks by power unit type and 5 trip distance categories. The comparable travel distribution is shown in Figure 75.

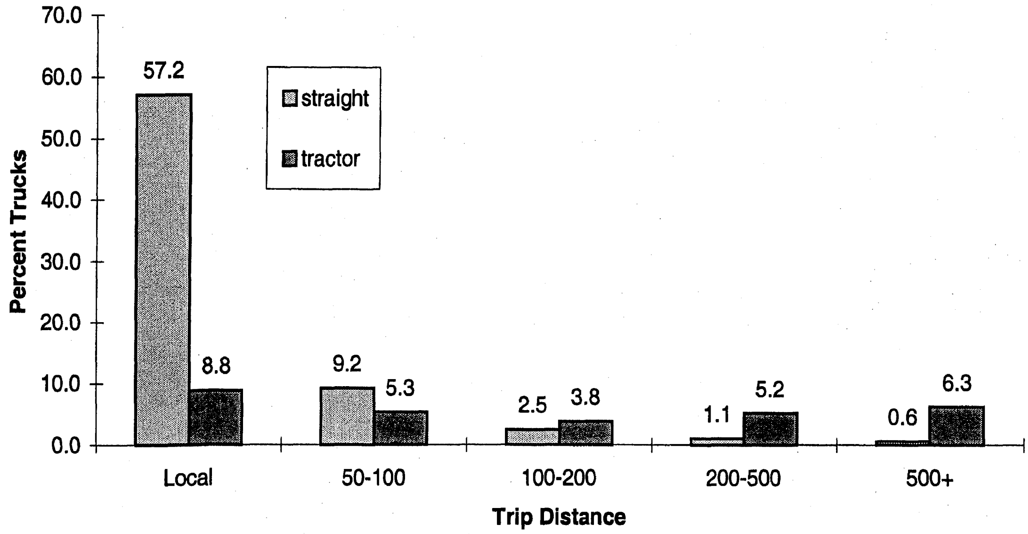

Figure 80
Distribution of Trucks by Power Unit type and Trip Distance (5 levels)
1992 Truck Inventory and Use Survey

The same distribution collapsed to 3 trip categories is shown in Figure 81, and the combined distribution including carrier type is shown in Figure 82. The comparable distributions of travel are Figure 78 and Figure 79. In general, the truck distributions are dominated by the large number of straight trucks in local service. These trucks far outnumber the tractors in long haul service in terms of registered vehicles.

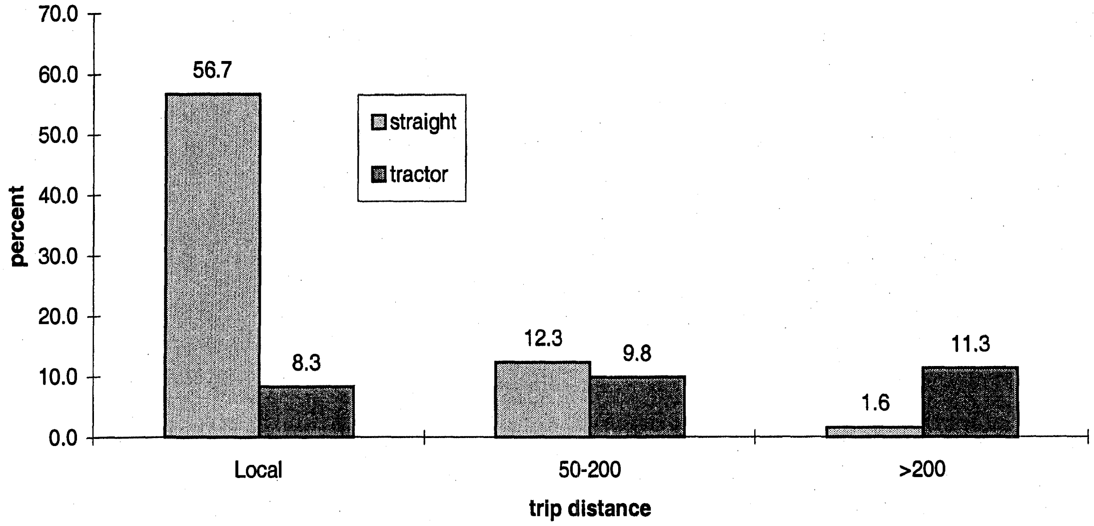

Figure 81
Distribution of Trucks by Power Unit type and Trip Distance (3 levels)
1992 Truck Inventory and Use Survey

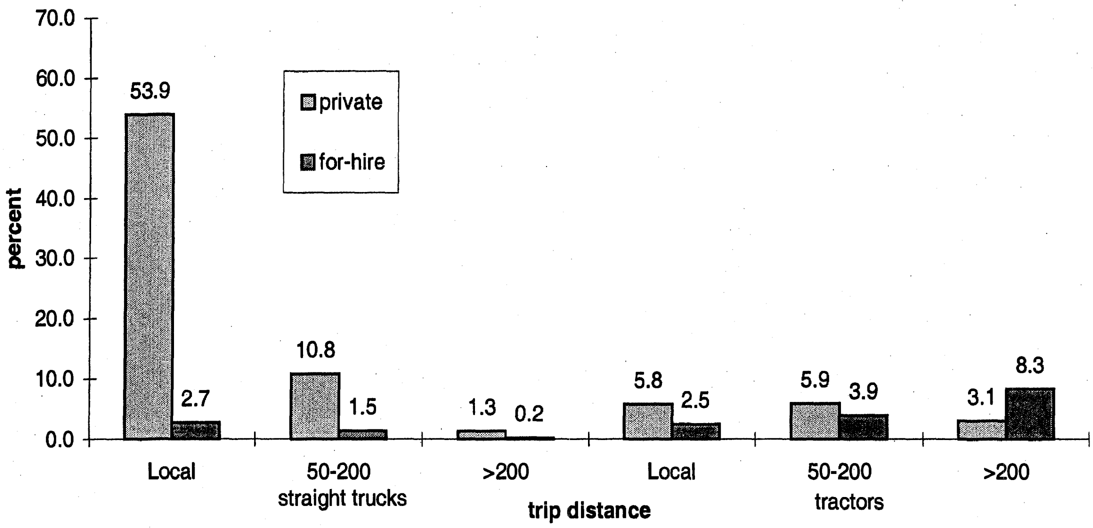

Figure 82
Distribution of Trucks by Power Unit type, Trip Distance, and Carrier Type
1992 Truck Inventory and Use Survey

1.2.3 Relative Risk Based on Vehicle Miles Traveled and Truck Population

This section combines the counts of trucks involved in fatal accidents from Section 1.1 with the truck travel and truck population estimates from the 1992 TIUS file from the previous section to calculate fatal accident involvement rates. The 1992 TIUS is based on vehicle registrations and does not include government owned vehicles, government owned trucks have also been excluded from the accident counts for the rate calculation. Government owned trucks were included in Section 1.1. Since only 2.2 percent of all medium and heavy trucks in the 1991 to 1996 TIFA files are coded as government owned, their exclusion does not change the distributions noticeably. The choice of accident years to combine with the 1992 TIUS data is dictated by the trip distance categories available in the TIFA file. Only the 1994 to 1996 TIFA data include the 5 level trip distance classification used in the 1992 TIUS file. Consequently, relative risk for the 5 level trip distance classification can only be obtained by combining the 1994–1996 TIFA data with the 1992 TIUS. Collapsing to the 3 level classification (used in the 1987 TIUS) allows use of the 1991–1996 TIFA data, providing a larger sample size. Obviously, these accident years are not an ideal match in time period to the 1992 TIUS. The absolute value of the rates changes somewhat (see the tables at the end). The absolute rates shown in the tables are based on an annual average accident count to correspond to the annual travel figures from TIUS. Note that the absolute rates are numerically quite similar in the 1994–1996 tables as compared to the 1991–1996. Also, the distributions across trip distance categories is quite stable. Thus, the relative risk figures are felt to be appropriate for both time periods.

The accident rates are presented as a relative risk so that the variations from category to category are emphasized and are comparable to the information presented in Section 1.1. The adjustment is accomplished by dividing each of the cell rates by the aggregate rate for the entire table—usually all medium and heavy trucks. The focus of this analysis is the variation from category to category, not the absolute value of the accident rates. However, the absolute values of the accident rates per 100 million vehicle miles traveled and per million registered trucks are given in tabular form at the end of this section. The relative risk based on truck travel and truck registrations are presented in pairs. The top figure on each page describes the overall risk of involvement in a fatal accident for all medium and heavy trucks. The bottom figure is limited to trucks with driver fatigue coded as a contributing factor and characterizes the variations in the risk of truck driver fatigue. All relative risk figures based on travel are presented first, followed by the same figures based on truck population. The counts of trucks involved in fatal accidents are exactly the same for both sets. All differences arise from the change in denominator. These differences in the exposure method used are all a consequence of differences in the average annual travel across the categories shown. These differences are substantial. There is a close association between the trip distance categories and average annual travel. Trucks in local service have the lowest annual mileage and trucks in long haul service tend to have the highest. Consequently, the variation in relative risk of involvement in a fatal accident looks very different depending on the choice of exposure measure, travel or truck population. But the variations in the relative risk of fatigue are essentially the same, regardless of the exposure method. This result is a consequence of the domination of the overall risk of fatigue by the probability of fatigue given involvement in a fatal accident (referred to as relative risk based on accident involvement in Section 1.1). Variations in the overall risk of fatal accident involvement are generally smaller in this analysis.

Care should be used when interpreting disaggregate accident rates. Cell rates do not sum to produce a combined rate as do counts. The rate of the combined cells must be calculated by first summing the numerators and denominators and then dividing these sums. The rate for a combination of cells will always fall between the individual cell values, but the result is a weighted average where the weighting factor is the denominator. Consequently, one cannot aggregate in a table of rates without knowing the corresponding values for the numerators and denominators.

The first pair, Figure 83 and Figure 84, show the relative risk based on travel for the 5 level trip distance variable using the 1994–1996 TIFA data and the 1992 TIUS. In the top figure, the overall risk of fatal accident involvement declines as trip distance increases. However, the risk of fatigue increases with increasing trip distance. Notice that the relative risk of fatigue based on travel looks similar in pattern to the relative risk of fatigue based on fatal accident involvement presented in Section 1.1. This result occurs because the variations in the overall risk of fatal accident involvement (shown in Figure 83) are numerically smaller than the variations risk based on accident involvement (probability of fatigue given involvement in a fatal accident). In this case, the relative risk based on accident involvement reveals the correct pattern of fatigue with trip distance, although the value of the relative risk figures is modified somewhat by the overall risk variation shown in Figure 83.

The next pair of figures, Figure 85 and Figure 86, add power unit type to the 5 level trip distance variable. The result is similar. Straight trucks operating on longer trips tend to have a higher fatigue risk than tractors in the same trip category.

The 3 level trip distance variable is shown for the 1991–1996 TIFA data in Figure 87 through Figure 94. Similar variations in risk with trip distance and power unit type are shown. The risk of fatigue increases with trip distance, and straight trucks tend to have a higher risk of fatigue than tractors on the longer trips. Carrier type (private/ for-hire) is examined in Figure 91 and Figure 92. Overall, for-hire carriers have a 50 percent higher overall fatal accident involvement rate per mile traveled. Based on Figure 91, the rate for for-hire carriers is higher in every category. The risk of fatigue is also higher for for-hire carriers in every category except one, as shown in Figure 92.

The rates per truck are shown in Figure 95 through Figure 106. As discussed earlier, overall rates change substantially with registered trucks as the exposure measure due to differences in average annual travel, but the patterns of variation in the risk of fatigue are essentially the same as those calculated with travel as the exposure measure. The actual rates based on travel are shown in Table 19 through Table 26. Per truck rates are in Table 27 through Table 33.

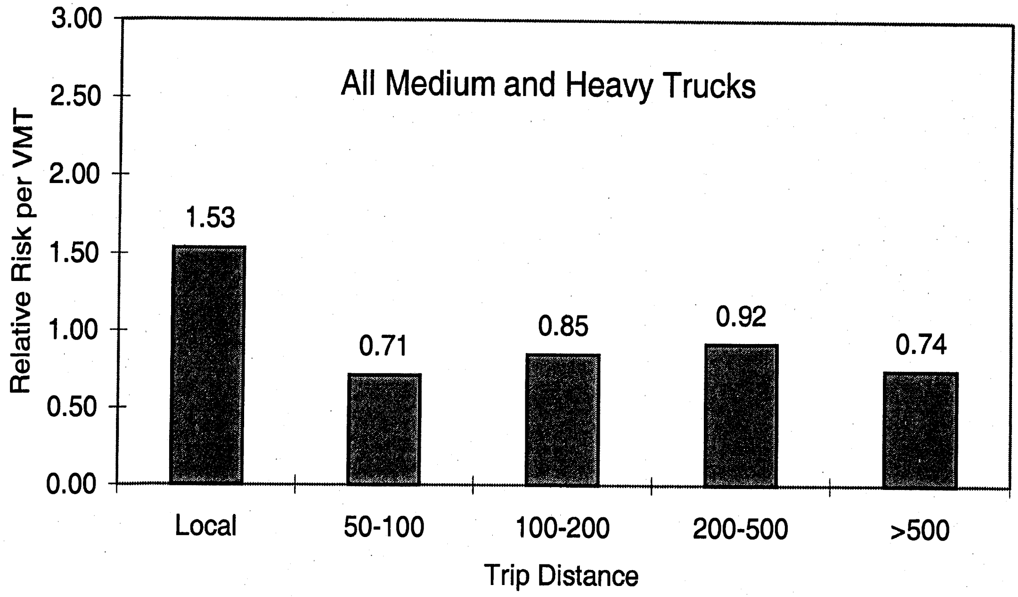

Figure 83
Relative Risk by Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

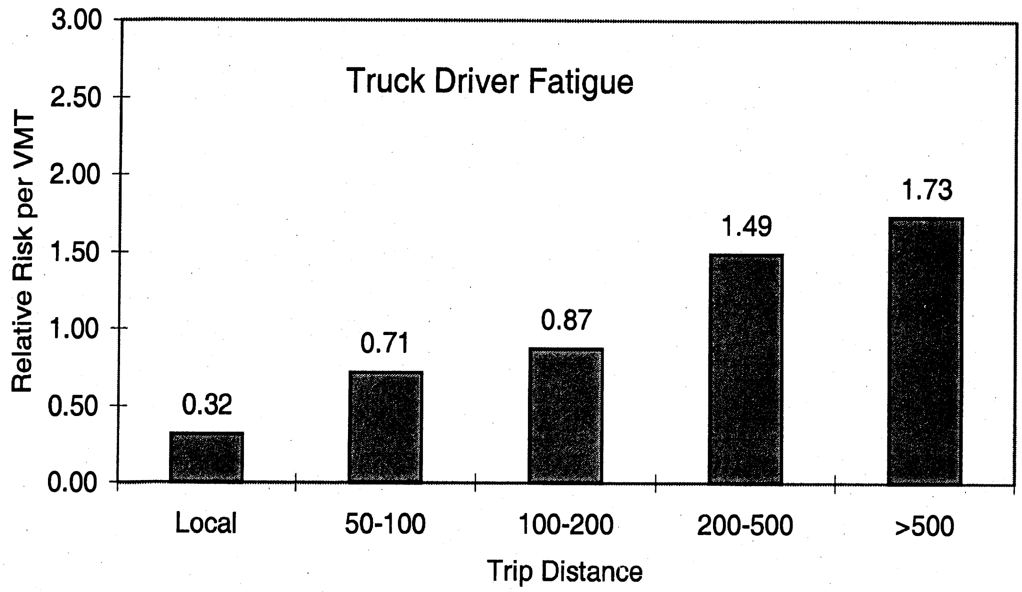

Figure 84
Relative Risk of Truck Driver Fatigue by Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

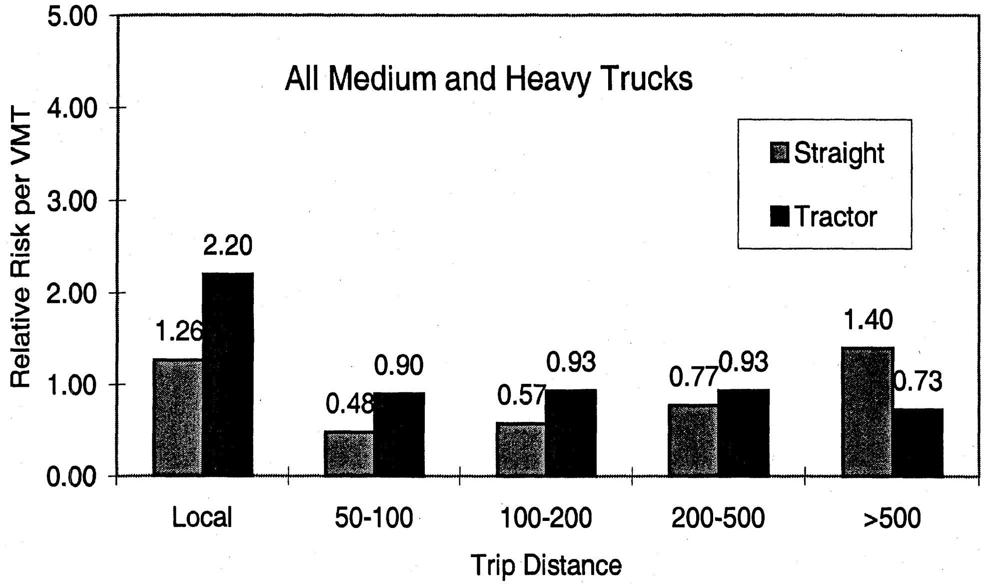

Figure 85
Relative Risk by Power Unit Type and Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

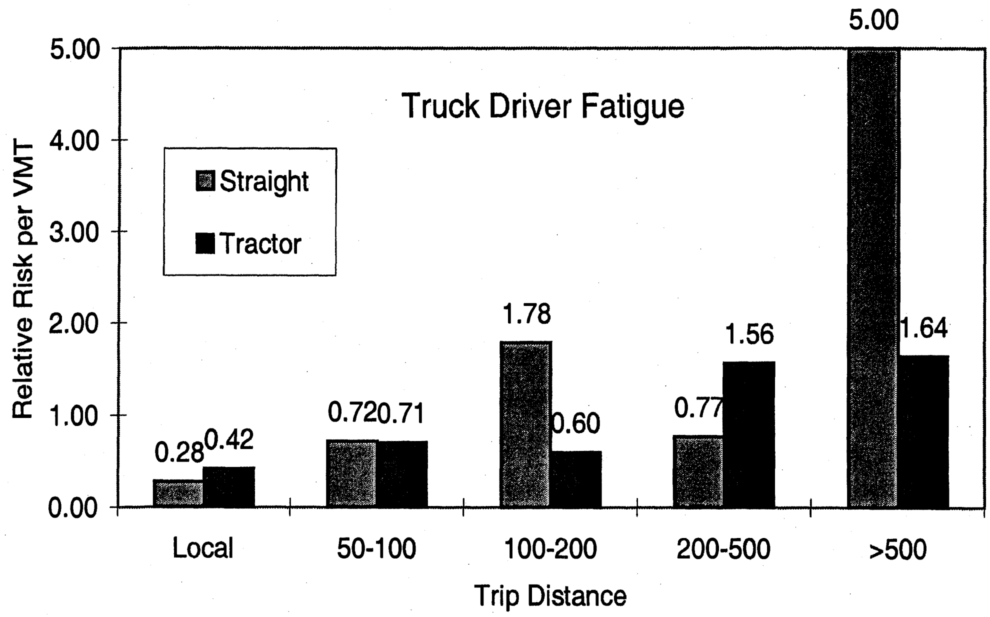

Figure 86
Relative Risk of Truck Driver Fatigue by Power Unit Type and Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

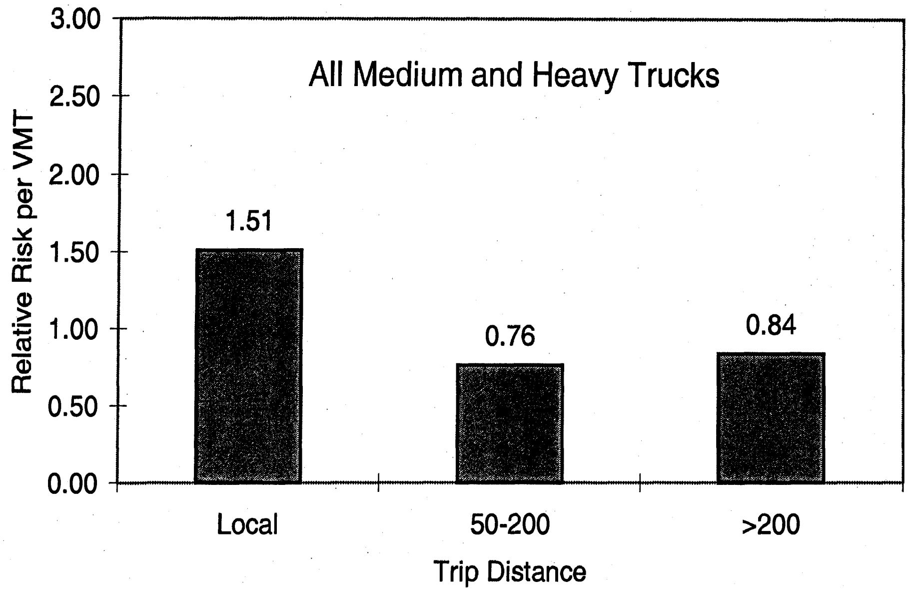

Figure 87
Relative Risk by Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

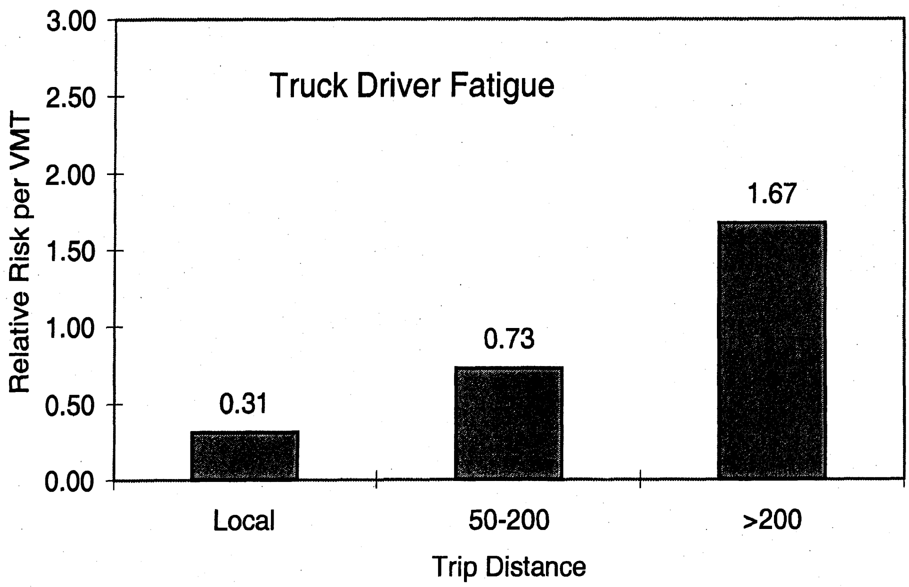

Figure 88
Relative Risk of Truck Driver Fatigue and Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

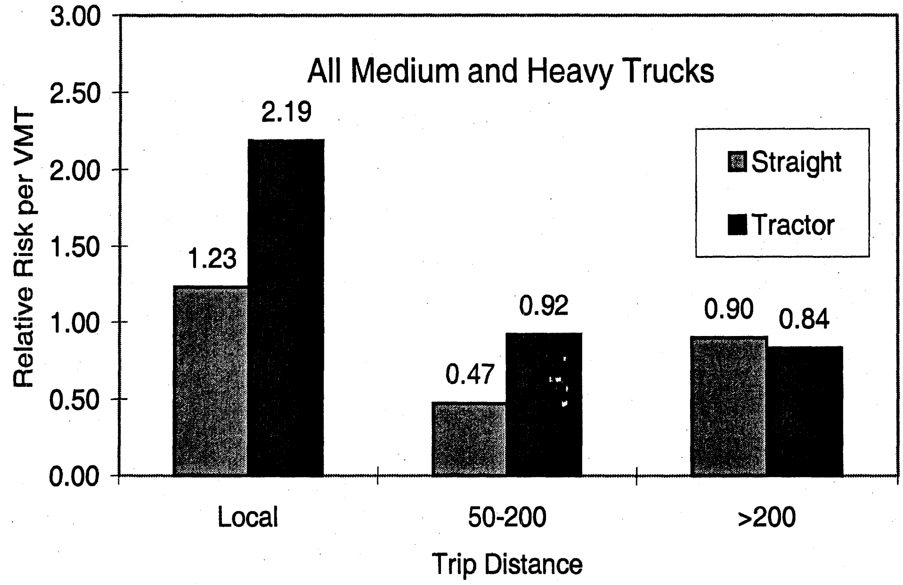

Figure 89
Relative Risk by Power Unit Type and Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

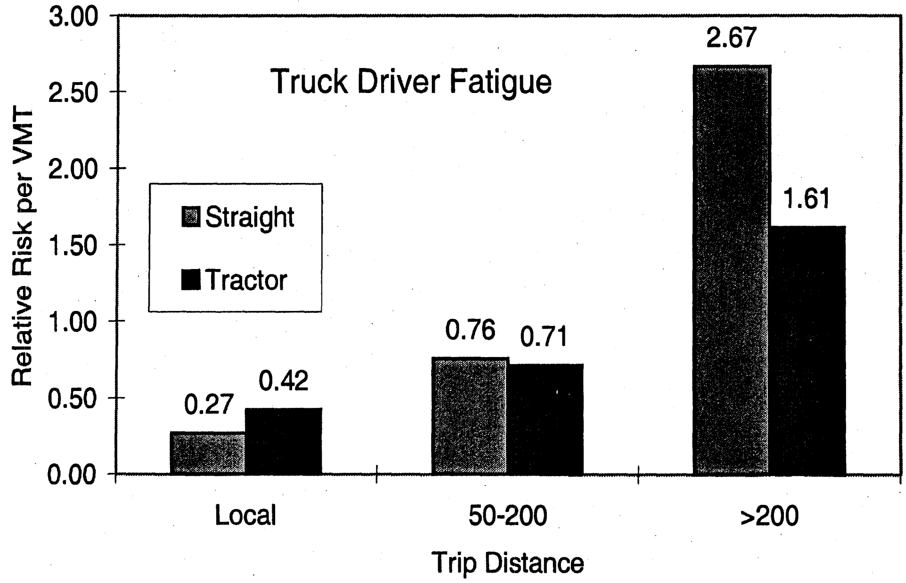

Figure 90
Relative Risk of Truck Driver Fatigue by Power Unit Type and Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

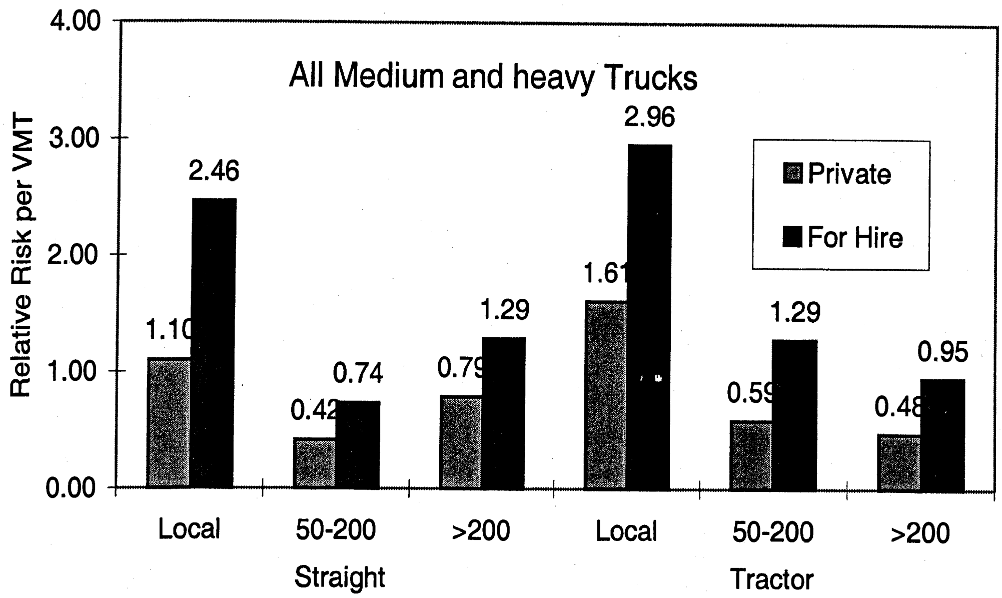

Figure 91
Relative Risk by Power Unit Type and Trip Distance versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

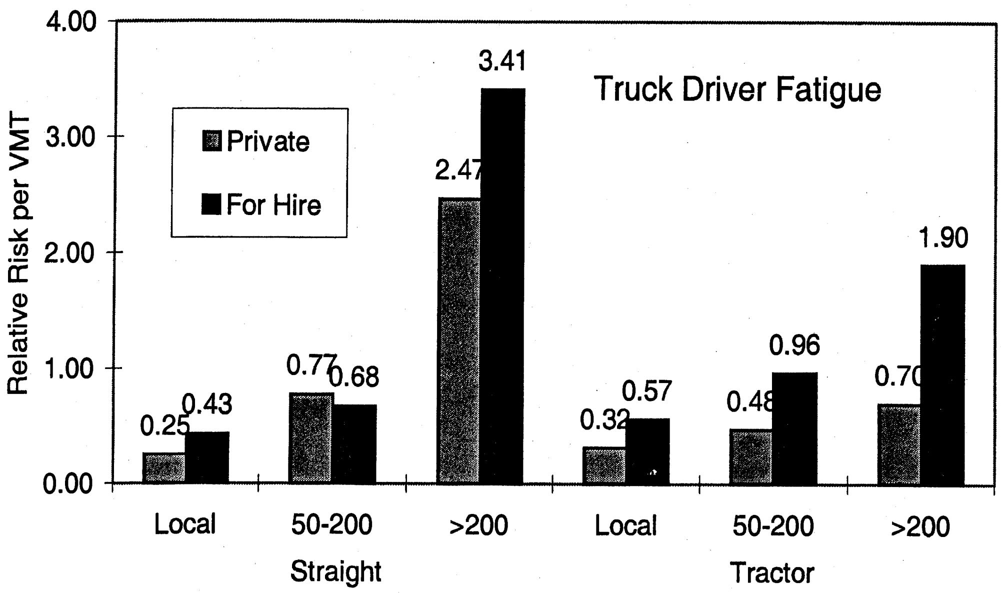

Figure 92
Relative Risk of Truck Driver Fatigue by Power Unit Type and Trip Distance versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

The last 2 figures in this series, Figure 93 and Figure 94 are somewhat different in format. Here the accidents are classified as truck occupant fatalities or non-truck fatalities. If the only fatalities in the accident were truck occupants, then the case is classified as a truck fatality. If anyone not in the truck received fatal injuries, the case is coded non-truck. This classification was also presented in Section 1.1. This classification requires a different treatment for exposure. Exposure cannot be classified based on an accident outcome like this. The appropriate exposure measure for both truck and nontruck fatalities is all truck travel in each power unit type and trip distance category. For the truck/non-truck classification, only the numerator changes. A relative risk cannot be calculated in the same manner, so the actual rates are shown. In this case, the truck and non-truck rates sum to the overall rate within each power unit type and trip distance category. Consequently, the result is that same as observed in Section1.1. Whereas 87 percent of all fatal truck involvement result in a nontruck fatality, nearly 70 percent of the fatigue involvements result in fatality to truck occupants only. The rates per travel and per truck are presented so that the impact of HOS options can be calculated separately for truck and non-truck fatalities. The same approach is taken in the next series when the rates per truck are classified as truck and non-truck fatalities.

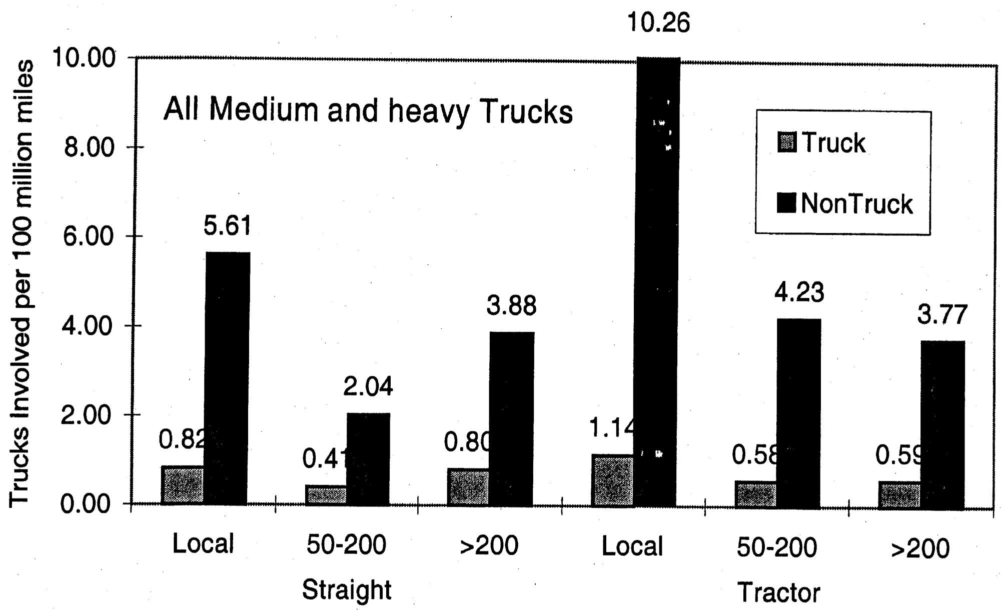

Figure 93
Truck versus Nontruck Fatalities by Power Unit Type and Trip Distance
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

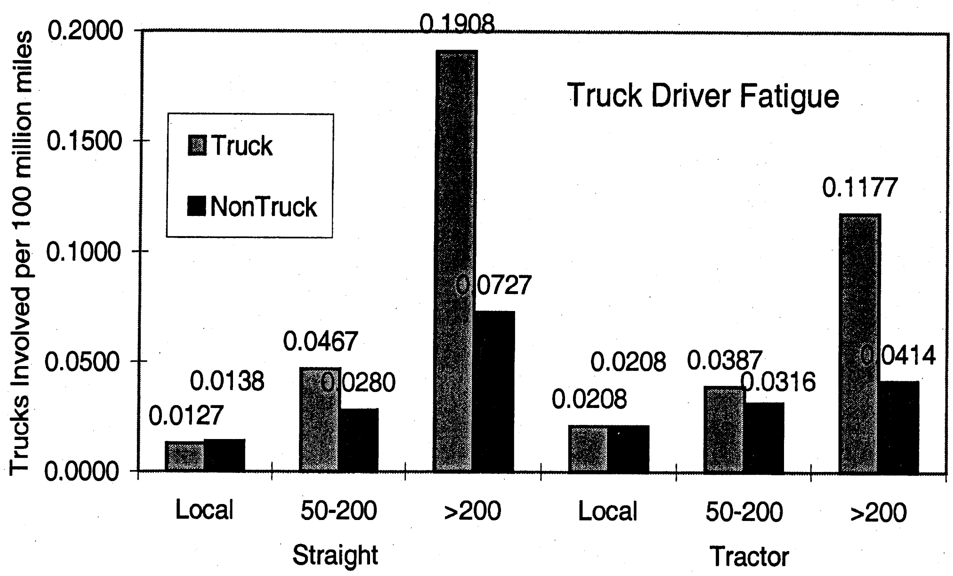

Figure 94
Truck Driver Fatigue in Truck versus Nontruck Fatalities:
by Power Unit Type and Trip Distance
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

Rates per Truck

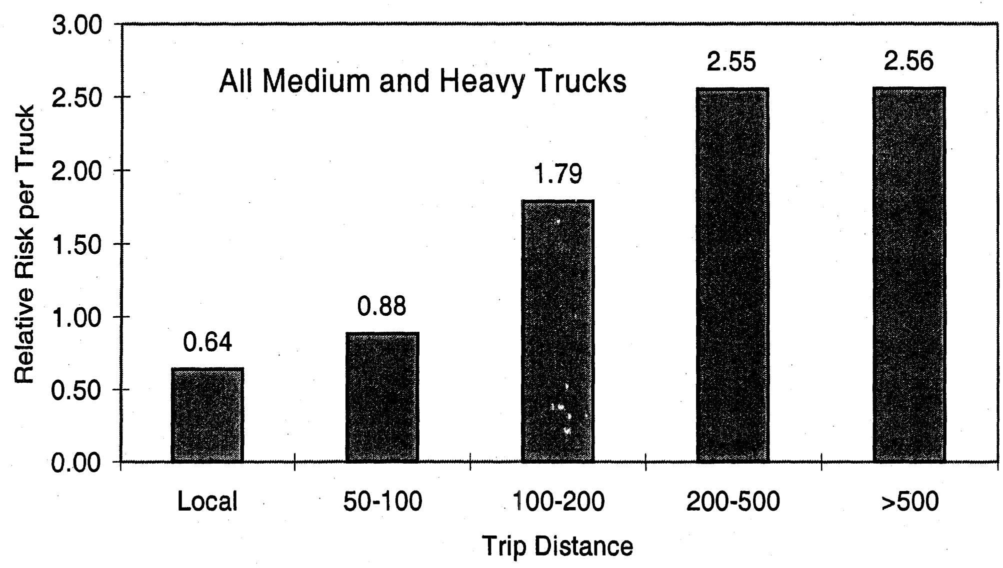

Figure 95
Relative Risk per Truck by Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

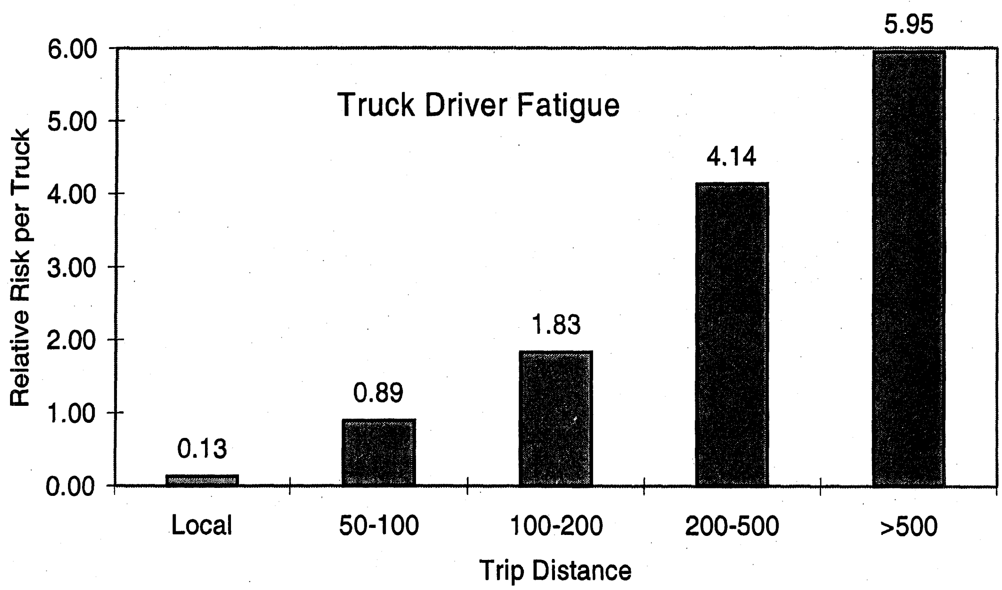

Figure 96
Relative Risk per Truck of Truck Driver Fatigue by Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

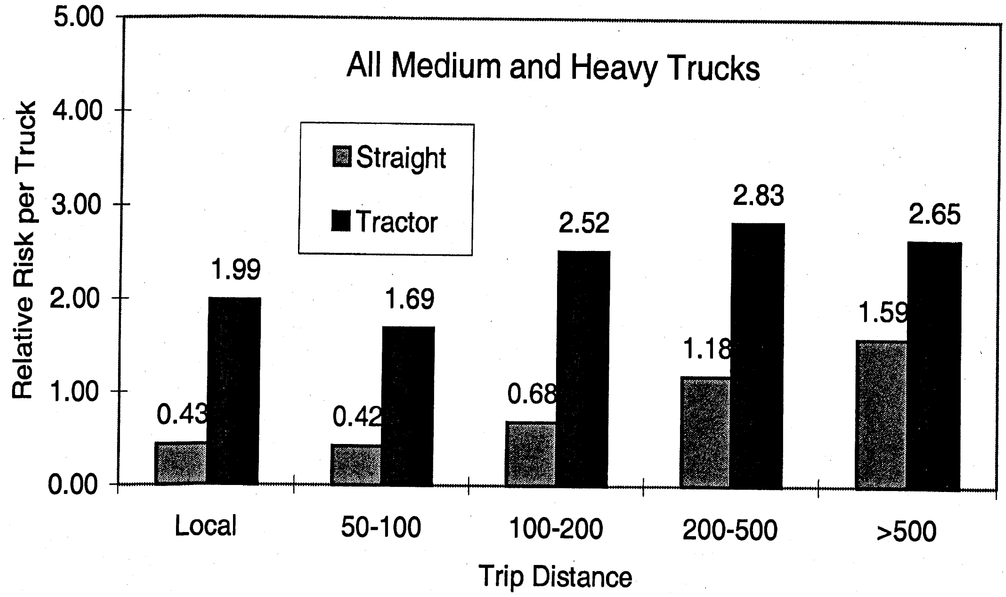

Figure 97
Relative Risk per Truck by Power Unit Type and Trip Distance (5 level)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

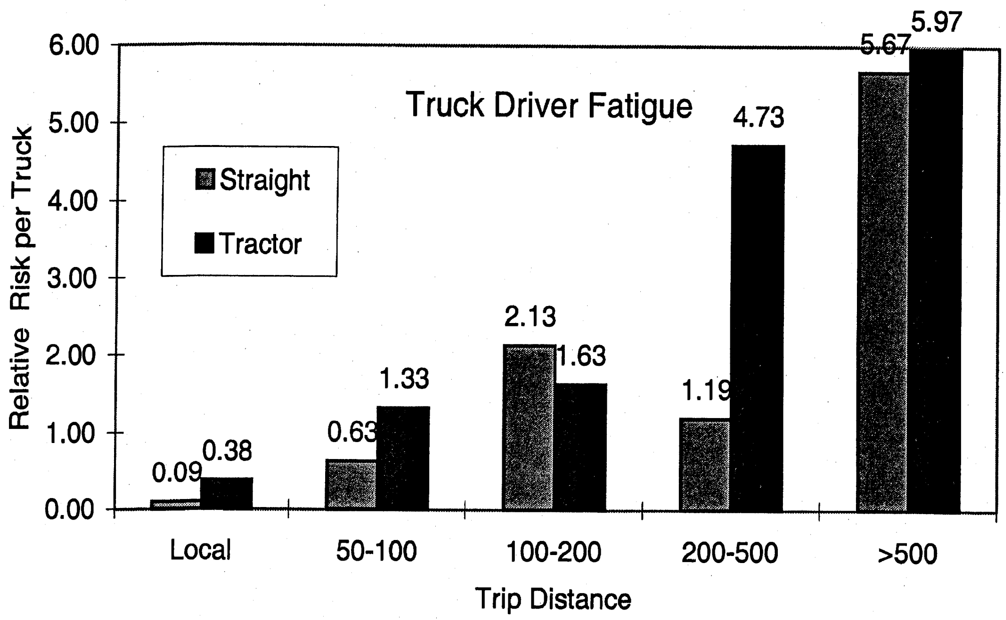

Figure 98
Relative Risk per Truck of Truck Driver Fatigue by Power Unit Type
and Trip Distance (5 level), Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

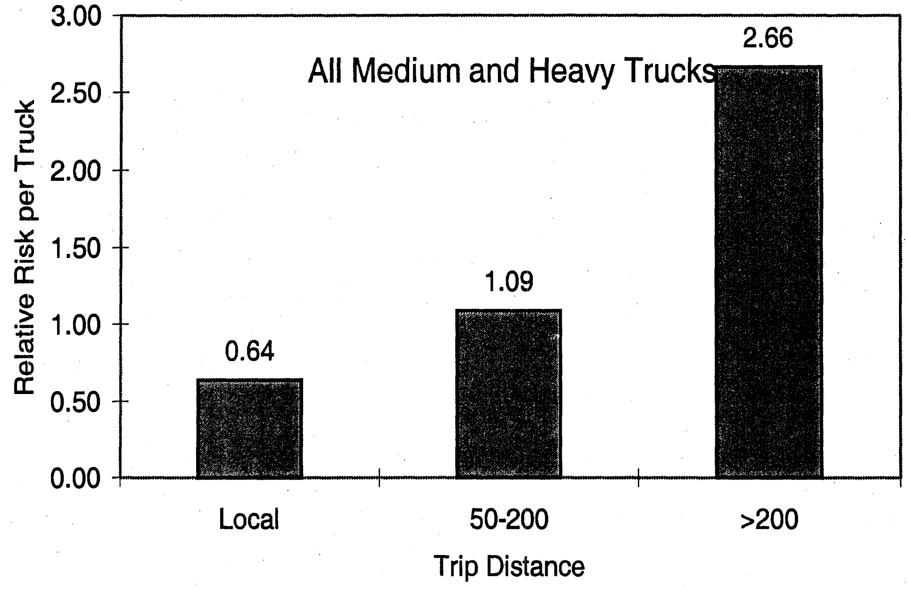

Figure 99
Relative Risk per Truck by Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

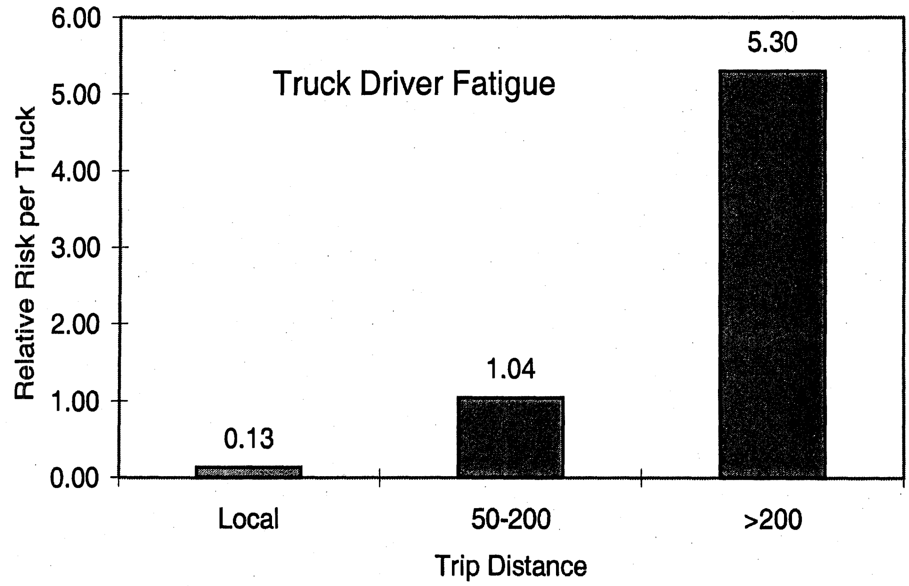

Figure 100
Relative Risk per Truck of Truck Driver Fatigue and Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

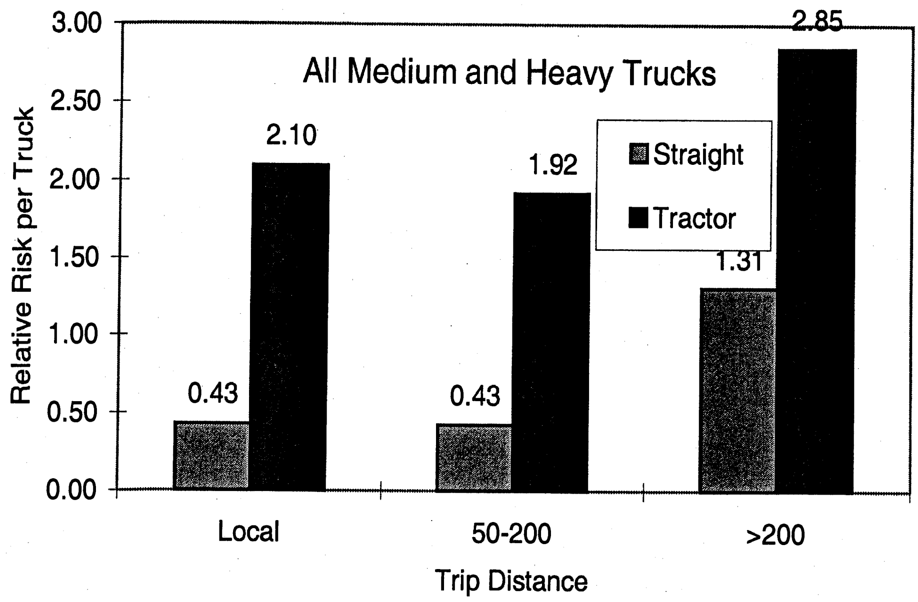

Figure 101
Relative Risk per Truck by Power Unit Type and Trip Distance (3 level)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

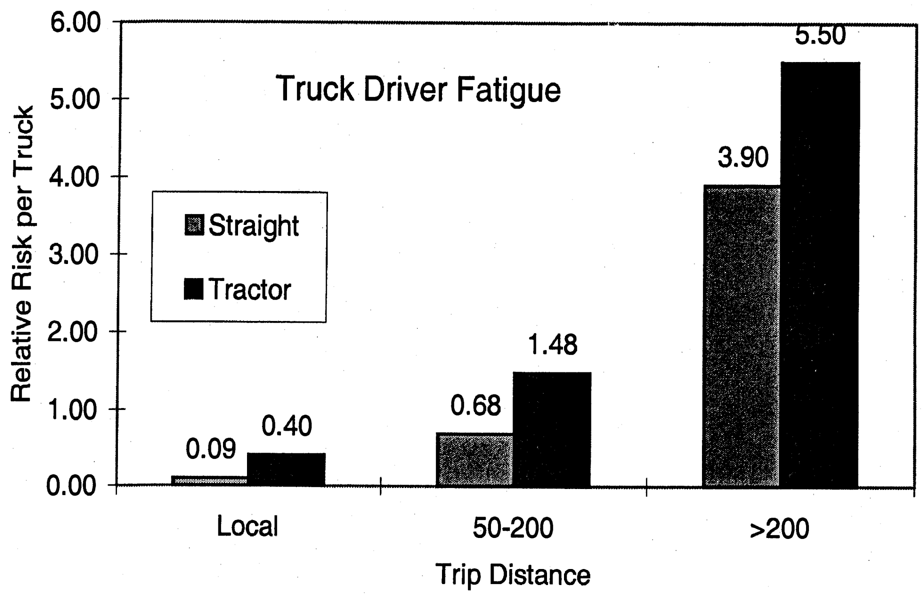

Figure 102
Relative Risk per Truck of Truck Driver Fatigue by Power Unit Type
and Trip Distance (3 level), Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

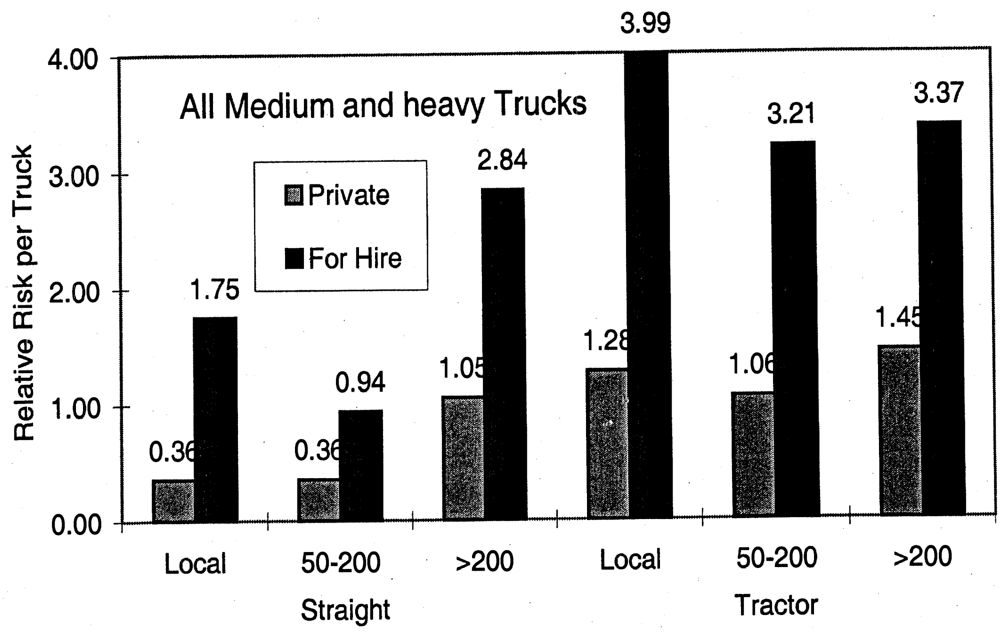

Figure 103
Relative Risk per Truck by Power Unit Type and Trip Distance (6 levels) versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

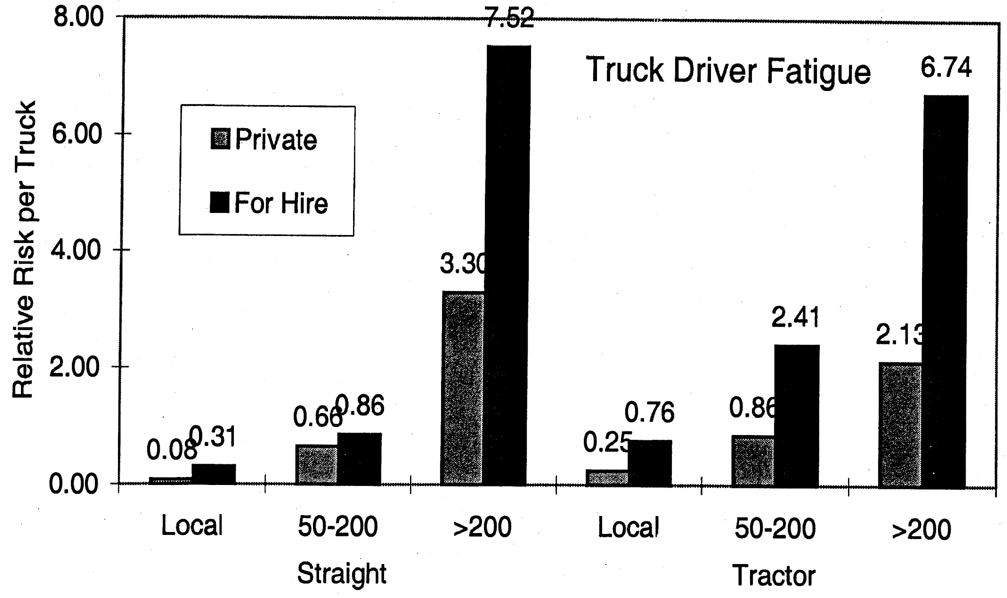

Figure 104
Relative Risk per Truck of Truck Driver Fatigue by Power Unit Type and Trip Distance versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

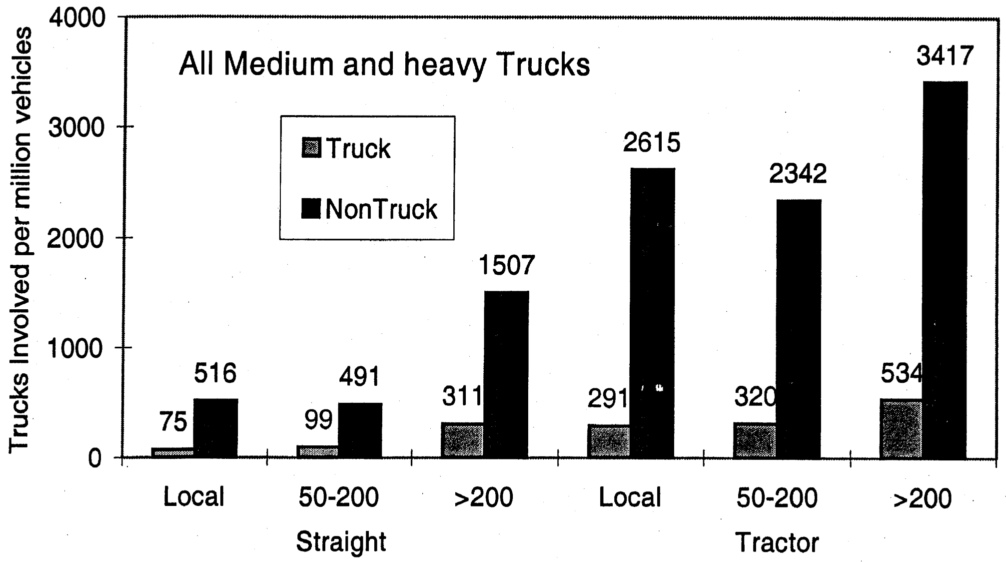

Figure 105
Truck versus Nontruck Fatalities by Power Unit Type and Trip Distance (6 levels) Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

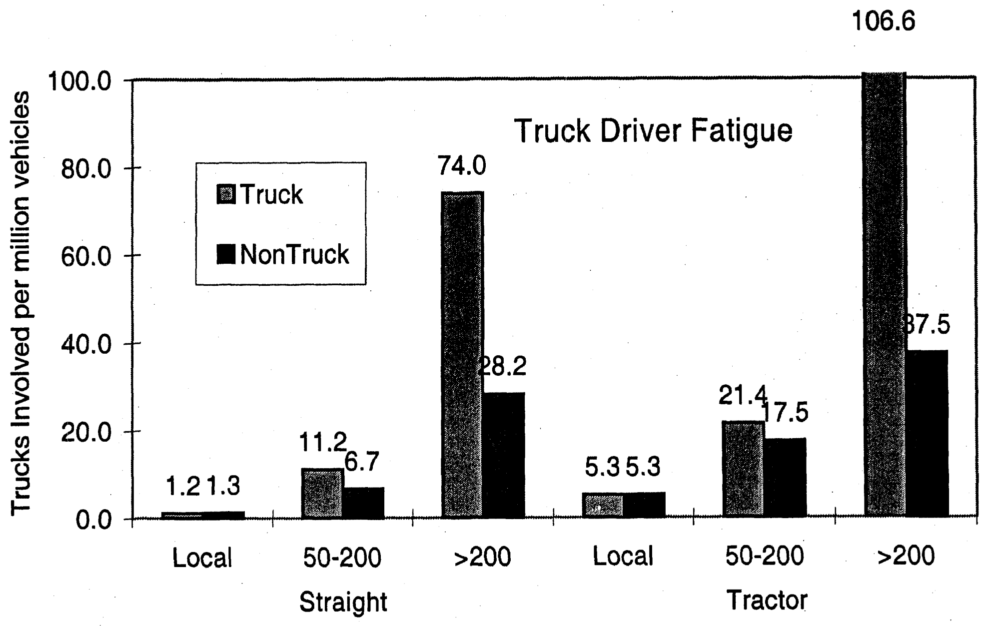

Figure 106
Truck Driver Fatigue in Truck versus Nontruck Fatalities
by Power Unit Type and Trip Distance
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

Tables Of Accidents Rates per VMT

Table 19
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled by Power Unit Type and Trip Distance (5 levels)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

	Trip Distance					
Rate	Local	50-100	100-200	200-500	>500	Total
Straight	5.65	2.13	2.55	3.44	6.26	4.32
Tractor	9.84	4.03	4.17	4.18	3.25	4.54
Total	7.00	3.24	3.88	4.20	3.40	4.57

Table 20
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled, Truck Driver Fatigue by Power Unit Type and Trip Distance (5 levels)
Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

	Trip Distance					
Rate	Local	50-100	100-200	200-500	>500	Total
Straight	0.0234	0.0613	0.1513	0.0654	0.4242	0.0500
Tractor	0.0354	0.0599	0.0512	0.1325	0.1388	0.1019
Total	0.0274	0.0617	0.0753	0.1287	0.1496	0.0864

Table 21
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled by Power Unit Type and Trip Distance (3 levels)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Trip Distance			
Rate	Local	50-200	>200	Total
Straight	6.29	2.40	4.59	4.83
Tractor	11.17	4.71	4.27	5.25
Total	7.86	3.98	4.37	5.21

Table 22
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled, Truck Driver Fatigue by Power Unit Type and Trip Distance (3 levels)
Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Trip Distance			
Rate	Local	50-200	>200	Total
Straight	0.0262	0.0740	0.2609	0.0571
Tractor	0.0412	0.0696	0.1575	0.1177
Total	0.0309	0.0719	0.1649	0.0986

Table 23
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled by Power Unit Type and Trip Distance (6 levels) versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Straight			Tractor			
Rate	Local	50-200	>200	Local	50-200	>200	Total
Private	5.54	2.11	3.97	8.15	2.96	2.40	4.04
For Hire	12.43	3.72	6.51	14.94	6.49	4.80	6.18
Total	6.22	2.39	4.55	11.01	4.66	4.23	5.05

Table 24
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled, Truck Driver Fatigue by Power Unit Type and Trip Distance (6 levels) versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Straight			Tractor			
Rate	Local	50-200	>200	Local	50-200	>200	Total
Private	0.0244	0.0755	0.2404	0.0310	0.0466	0.0683	0.0544
For Hire	0.0423	0.0658	0.3327	0.0551	0.0940	0.1854	0.1465
Total	0.0262	0.0739	0.2603	0.0411	0.0695	0.1572	0.0975

Table 25
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled, Truck versus Nontruck Fatalities by Power Unit Type and Trip Distance (6 levels) versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Straight			Tractor			
Rate	Local	50-200	>200	Local	50-200	>200	Total
Truck	0.82	0.41	0.80	1.14	0.58	0.59	0.66
NonTruck	5.61	2.04	3.88	10.26	4.23	3.77	4.55
Total	6.43	2.46	4.71	11.42	4.82	4.36	5.22

Table 26
Trucks Involved in Fatal Accidents per 100 Million Vehicle Miles Traveled, Truck Driver Fatigue in Truck versus Nontruck Fatalities by Power Unit Type and Trip Distance (6 levels) versus Carrier Type Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Straight			Tractor			
Rate	Local	50-200	>200	Local	50-200	>200	Total
Truck	0.0127	0.0467	0.1908	0.0208	0.0387	0.1177	0.0683
NonTruck	0.0138	0.0280	0.0727	0.0208	0.0316	0.0414	0.0303
Total	0.0265	0.0748	0.2634	0.0416	0.0703	0.1591	0.0986

Tables Of Accidents Rates per Truck

Table 27
Trucks Involved in Fatal Accidents per Million Registered Trucks by Power Unit Type and Trip Distance (5 levels) Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

	Trip Distance					
Rate	Local	50-100	100-200	200-500	>500	Total
Straight	515	497	811	1408	1887	537
Tractor	2367	2010	2999	3368	3151	2747
Total	777	1073	2170	3099	3104	1214

Table 28
Trucks Involved in Fatal Accidents per Million Registered Trucks, Truck Driver Fatigue by Power Unit Type and Trip Distance (5 levels) Trucks Involved in Fatal Accidents 1994-1996 and 1992 TIUS

	Trip Distance					
Rate	Local	50-100	100-200	200-500	>500	Total
Straight	2.1	14.3	48.1	26.8	127.9	6.2
Tractor	8.5	29.9	36.8	106.7	134.6	61.6
Total	3.0	20.4	42.1	95.0	136.6	23.0

Table 29
Trucks Involved in Fatal Accidents per Million Registered Trucks by Power Unit Type and Trip Distance (3 levels) Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Trip Distance			
Rate	Local	50-200	>200	Total
Straight	579	577	1780	600
Tractor	2845	2605	3867	3171
Total	887	1506	3688	1385

Table XX: Trucks Involved in Fatal Accidents per Million Registered Trucks, Truck Driver Fatigue by Power Unit Type and Trip Distance (3 levels) Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

	Trip Distance			
Rate	Local	50-200	>200	Total
Straight	2.4	17.8	101.2	7.1
Tractor	10.5	38.5	142.7	71.1
Total	3.5	27.2	139.0	26.2

Table 30

Trucks Involved in Fatal Accidents per Million Registered Trucks by Power Unit Type and Trip Distance (6 levels) versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

		Straight			Tractor		
Rate	Local	50-200	>200	Local	50-200	>200	Total
Private	482	478	1412	1716	1419	1940	707
For Hire	2348	1266	3812	5355	4301	4523	4020
Total	572	573	1766	2805	2580	3829	1341

Table 31

Trucks Involved in Fatal Accidents per Million Registered Trucks, Truck Driver Fatigue by Power Unit Type and Trip Distance (6 levels) versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

		Straight			Tractor		
Rate	Local	50-200	>200	Local	50-200	>200	Total
Private	2.1	17.1	85.4	6.5	22.3	55.3	9.5
For Hire	8.0	22.4	194.7	19.8	62.4	174.6	95.3
Total	2.4	17.7	101.0	10.5	38.4	142.4	25.9

Table 32

Trucks Involved in Fatal Accidents per Million Registered Trucks, Truck versus Nontruck Fatalities by Power Unit Type and Trip Distance (6 levels) versus Carrier Type, Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

		Straight			Tractor		
Rate	Local	50-200	>200	Local	50-200	>200	Total
Truck	75	99	311	291	320	534	176
NonTruck	516	491	1507	2615	2342	3417	1209
Total	591	590	1829	2909	2664	3954	1387

Table 33

Trucks Involved in Fatal Accidents per Million Registered Trucks, Truck Driver Fatigue in Truck versus Nontruck Fatalities by Power Unit Type and Trip Distance (6 levels) versus Carrier Type Trucks Involved in Fatal Accidents 1991-1996 and 1992 TIUS

		Straight			Tractor		
Rate	Local	50-200	>200	Local	50-200	>200	Total
Truck	1.2	11.2	74.0	5.3	21.4	106.6	18.2
NonTruck	1.3	6.7	28.2	5.3	17.5	37.5	8.1
Total	2.4	18.0	102.2	10.6	38.9	144.1	26.2

1.2.4 Discussion

Fatal accident involvement rates per 100 million vehicles miles traveled and per million registered trucks were calculated using the 1991–1996 ITFA data and the 1992 TIUS data. These rates may be useful to estimate the safety impact of the HOS options. The results also illustrate the variation in the risk of truck driver fatigue for the different operating environments and industry segments that can be identified in both the TIFA and TIUS files. These factors are limited to power unit type (straight/tractor), trip distance, and carrier type (private/for-hire). Missing data on the variable in the 1992 TIUS identifying interstate carriers was so large that this information is not usable. Exposure data are not available on other important factors such as time of day and hours driving.

Three measures of risk were explored. The probability of fatigue given involvement in a fatal accident was scaled by the overall probability of fatigue and presented as the relative risk of fatigue, given involvement in a fatal accident. This calculation requires only accident data. This measure is of interest because time of day, hours driving, and other factors are available in the TIFA data, but exposure information is not available. For the factors available in both TIFA and TIUS, two accident rates were calculated. The first is the overall rate (per 100 million miles traveled) for involvement in any fatal accident, and the second is the rate for only truck driver fatigue when involved in a fatal accident. As discussed in Section 1.1, these three rates are related as follows:

Relative risk of fatigue in a fatal accident = (relative risk of fatal accident involvement) x (relative risk of fatigue given fatal involvement)

This relationship is illustrated in Table 34. The rates in each row were calculated as described. The table illustrates that in each column, the bottom row is equal to the product of the first two rows. The relevance of this table is to assess whether the first row, that is based only on accident data, provides useful information on the risk of fatigue based on exposure, as shown in the last row. For the variables available, it seems that it does. The variation in relative risk in the first row is quite similar to the last row.

Table 34
Relation of Relative Risk Measures

Risk	Straight Local	Straight 50-200	Straight >200	Tractor Local	Tractor 50-200	Tractor >200	Total
Risk of fatigue given fatal accident involvement	0.22	1.61	2.97	0.19	0.77	1.93	1.00
Risk of fatal accident involvement per vmt	1.23	0.47	0.90	2.19	0.92	0.84	1.00
Risk of fatigue per vmt	0.27	0.76	2.67	0.42	0.71	1.61	1.00

This result occurs because the variation in risk in the first row is larger than in the second, a range of about 15:1 as compared to about 4:1. There are only two columns, straight trucks in the 50-100 category and local tractors where the second row significantly modifies the risk values from the first row. However, the overall pattern remains the same. This result suggests that the relative risk of fatigue given involvement in a fatal accident can provide useful information about the overall risk of fatigue for factors not available in existing exposure data.

The combination of the TIFA and TIUS data allowed rates per 100 million vehicle miles traveled and per million trucks for truck driver fatigue involvement in fatal accidents to be calculated for each combination of 3 important factors: power unit type (straight/tractor), trip distance, and carrier type (private/for-hire). Similar patterns in the relationship of these factors to the risk of fatigue were found in both the rates per travel and per truck. Trip distance, as might be expected, shows a substantial affect. Looking at the 5 level classification, trips with one way distances of 200–500 miles and trips over 500 miles one way both show substantial over involvement, 1.49 and 1.73 respectively. Underlying factors that are associated with trip distance are more likely to be responsible to the increased risk of fatigue on longer trips. Two such factors examined in Section 1.1 are time of day and hours driving. Local trips occur primarily during the daylight (and presumably with more sleep at night) whereas long haul trips involve more night travel. Local travel also seldom requires more than 8 hours of driving while long haul trips are more likely to involve more than 8 hours driving.

In addition to trip distance, power unit type is also associated with the risk of truck driver fatigue per mile traveled or per truck. Straight trucks and tractors both have relatively low risks of fatigue involvement in local and short trips. However, straight trucks on long trips have a substantially higher risk of fatigue than tractors. The results are somewhat mixed in the 5 level trip distance classification, but the fatigue risk for straight trucks is 66 percent higher than tractors in trips over 200 miles (one way). While tractors are better designed for long haul service, a more likely explanation is that straight truck drivers are less experienced in long haul trips and the associated fatigue than tractor drivers. Recall from Section 1.1 that straight trucks on trips greater than 200 miles account for less than 5 percent of all truck driver fatigue in fatal accidents. As can be seen in the earlier part of this section, the exposure of straight trucks in long haul service is very low.

Carrier type is the last factor that could be examined with exposure based rates. This factor shows the strongest association with fatigue. Overall the truck driver fatigue rate per mile traveled for for-hire carrier is nearly 3 time that of private carriers. This difference is in part due to the large number of straight trucks in local service operated by private carriers. However, for-hire tractors in long haul service (trips over 200 miles one way) also have a risk of fatigue that is 2.7 time that of private carriers on a per mile basis. Results from Section 1.1 show that for-hire carriers in interstate service are involved in about 3 time as many fatal accidents at night as private carriers, and the relative risk of fatigue given involvement in a fatal accident from midnight to 6am is 3 to 5 time higher for interstate for-hire carriers than interstate private carrier. There may be other factors associated with for-hire carriers such as irregular shifts or longer work weeks that may contribute to fatigue, but cannot be addressed in the TIFA or TIUS data.

Separate sets of rates were calculated using both travel (100 million vehicle miles traveled) and truck population (million registered trucks) as exposure measures. These two measures differ substantially because there is wide variation in annual mileage ranging from straight trucks in local service to long haul tractors. Consequently, the overall rates for involvement in any fatal accident look quite different depending on the exposure measure used. The interesting finding is that the risk of fatigue when involved in a fatal accident follows essentially the same pattern regardless of the exposure measure used. Again, this result is a consequence of the strength of the relationship of fatigue to the factors examined. This finding underscores the importance of the link between the various operating environments and fatigue.

1.3: Effects on Drivers and Motor Carriers

Task 1.3 was produced by a team of economists associated with the University of Michigan Institute of Labor and Industrial Relations (ILIR). The team worked individually and in small groups and collaborated together in several teleconferences. An important and unique contribution has been provided by data collected by the University of Michigan Trucking Industry Program (UMTIP) Driver Survey. These data were collected by Dr. Dale Belman of the University of Wisconsin - Milwaukee and Dr. Kristin Monaco of the University of Wisconsin - Eau Claire, with funding and support from UMTIP. Data manipulation for this report based on the UMTIP Driver Survey was provided by Dr. Monaco. Dr. Belzer did the final writing, along with integrative work. Some sections, as originally provided by contributors, were modified in significant respects by Dr. Belzer, so he is responsible for errors. Research assistance was provided by Michael Dover of ILIR.

Section 1.3.1 was written primarily by Dr. Belzer, based on data from the Driver Survey. These data provide an important baseline on truck driver wages, hours, and working conditions. They show that on average drivers do not comply with current hours of service regulations, suggesting a major cost for the implementation of regulatory option A, the current system. The data were collected at truck stops in five Midwest states, randomly selected and weighted for size by truck stop traffic. Drivers were selected at random in each truck stop in such as a proportion to create an even sampling frame. Survey assistance for the Driver Survey was provided by the University of Michigan Institute for Social Research, a premier survey agency.

Section 1.3.2 was written in two sections. The first section was produced by Dr. Donald Grimes and Dr. George Fulton of the University of Michigan ILIR. This analysis uses several sources, including the Current Population Survey (CPS), the UMTIP Driver Survey, the Truck Inventory and Use Survey (TIUS), and Form M of interstate motor carrier operations, currently collected by the US DOT Bureau of Transportation Statistics. Help in estimating the number of owner operators was received from the Owner Operator Independent Driver Association (OOIDA). This section estimates the cost of achieving compliance with current law. While we do not estimate enforcement costs themselves (far beyond our mandate in this study) we do estimate what would happen if drivers actually complied with the law. The cost of bringing drivers into compliance with the existing regime most likely far outweighs the cost of changing regulatory regimes.

The second section of 1.3.2 was written primarily by Dr. Stephen Burks of ILIR. Dr. Burks received data analysis assistance and modeling collaboration from Dr. Monaco, as well as econometric assistance and advice from Dr. Daniel Lass and Dr. Dale Ballou of the University of Massachusetts. The regression models in this section allow us to provide some estimates of the social opportunity cost of the proposed policy changes. We find that the social cost of proposed changes in driver schedule regularity and night driving are modest.

Section 1.3.3 was written by Dr. Belzer. In this section we make some qualitative judgements about the kinds of changes that might result for the industry as a result of the proposed regulatory change.

1.3.1: Current Driver Experience Baseline.

The University of Michigan Trucking Industry Program (UMTIP) conducted a survey of drivers in 1997. UMTIP also is conducting a survey from the summer of 1998 through the end of spring in 1999. Both of these surveys collect information on driver hours of work, safety, sleep experience, and other factors. This task will be to evaluate that data to determine current practices of drivers: hours driven and worked, including characteristics of non-driving labor; number of miles driven; time of day; adherence to regulations; sleep experience; self-reported drowsy driving; and others. The survey shows, for example, that the median driver works 62 hours in a seven day week. The median local driver works 56.8 hours and the median over-the-road driver works 65. At the 90th percentile the figure is 95 hours, with local drivers at 91 hours and over-the-road drivers at 95 hours. The driver survey also includes detailed information on pay: whether time is paid or not, whether paid time is hourly or contingent on labor or a flat rate, and the level of pay for each driver category.

The underlying theory used for this study looks to the competitive marketplace to understand the economic pressures that determine the truck driver's work environment, so it is important to incorporate those market pressures in any evaluation of governmental regulatory efforts. The UMTIP driver survey provides a unique look at the current work environment of the over-the-road truck driver. The driver survey suggests to us that the truck drivers indeed work long hours, and the problem of long hours and irregular schedules correlate strongly with the extent to which drivers compete with each other to drive down wages and conditions.

The driver survey used a two-stage randomized design in five Midwest states. We selected truck stops at random from the population of truck stops in these states, stratified based on the number of parking spaces for trucks as a proxy for truck traffic. Subjects were chosen at random (every nth individual who walked through the door). The survey took approximately 45 minutes and we paid drivers $20 for their time. We experienced a response rate of 60% (including conversions for those who had insufficient time at the truck stop but whom we interviewed at home). An additional 6% response was achieved using a five minute questionnaire. We also conducted a fuel line survey to confirm sample validity, and achieved an 96% response rate on the fuel line. We currently are conducting a follow up to the original driver survey. Though we have had to reduce the number of survey administrations due to lack of funds, we believe we will continue to have a valid sampling frame. This second wave of surveys will cover a one-year period extending from summer 1998 through spring of 1999.

Miles

Table 35: Annual Miles

	Full Survey	Full Survey, Local Drivers	Full Survey, Regional Drivers	Full Survey, Long Haul Drivers
Mean	112,765	82,065	103,617	124,475
10th pct	60,000	25,000	50,000	78,000
25th pct	90,352	50,000	80,000	100,000
Median	110,000	80,000	100,000	120,000
75th pct	130,000	125,000	125,000	150,000
90th pct	160,000	130,000	145,600	170,000
	n=451	n=49	n=113	n=281

Table 35 above shows the trends for mileage driven by individual drivers.[1]

The average driver covers 112,765 miles annually, and long-haul drivers drive 124,475 miles. Averages exceed medians, demonstrating the extent to which high mileage figures dominate. Indeed, the top 25 percent of all drivers exceed 150,000 miles and ten percent exceed 170,000 miles, a quite extraordinary figure. The survey shows that owner operators drive substantially fewer miles than do company drivers, suggesting that the pressure on company drivers is greater than that on the owner-operators who need to pay off their equipment. The following table compares over-the-road drivers who work as employees with over-the-road drivers who own their trucks ("owner-operators"). Employee drivers drive 5.8 percent more miles than do owner-operators. Incidentally, since more than 17 percent of the drivers in our sample work for private carriers, and since few owner-operators (OOs) haul for private carriers, we suspect the over-the-road (OTR) employee drivers in the for-hire sector average a greater number of miles, increasing the gap between themselves and the owner-operators.

[1] For all mileage calculations the highest and lowest 1 percent have been trimmed to remove inappropriate outliers. For all wage calculations, the highest and lowest 5% have been trimmed both to remove outliers and to ensure that only those working a full year are included. We believe this trimming is necessary to get an accurate picture of driver effort level. In all cases the n for the "full survey" includes all of the drivers for whom valid data existed on all variables studied in this analysis. This is a different purpose than one might have when merely establishing a census. If we are awarded a contract for the definitive cost-benefit analysis, we revise the data set as appropriate.

Table 36: Annual Miles

	Full Survey, OTR drivers	Full Survey, OTR OOs
Mean	119,392	112,521
10th pct	72,000	62,400
25th pct	100,000	90,000
median	120,000	110,000
75th pct	140,000	135,000
90th pct	170,000	160,000
	n=287	n=114

In our regression sample, which for modeling purposes includes only those employee drivers paid by the mile, the average mileage is greater yet.

Table 37: Annual Miles

	Regression Sample, Mileage Paid Ees
mean	121,561
10th pct	75,000
25th pct	100,000
median	120,000
75th pct	140,000
90th pct	170,000
	n=201

As we will see throughout, unionization is associated with lower mileage output. Across all distance categories, union drivers run nearly 7 percent fewer miles.

Table 38: Annual Miles

	Full Survey, Union Ee drivers	Full Survey, Non-union Ee drivers
mean	106,694	114,548
10th pct	50,000	60,000
25th pct	90,000	100,000
median	100,000	118,000
75th pct	125,000	136,000
90th pct	150,000	160,000
	n=46	n=287

Hours

How does this translate into weekly hours of work? The driver survey shows that on average drivers worked 64.3 hours in the past seven days, including driving and on-duty-not-driving. The survey also shows, somewhat surprisingly, that local drivers work as many hours as do long-haul drivers. Since we collected our data at truck stops that generally were not in major metropolitan areas, and since drivers identified themselves in these categories, we suspect our local drivers are more like the "home base" drivers as suggested by the FHWA. With these data it is not possible (at least under these severe time constraints) to distinguish definitively between these two categories. Regardless, the data suggest a broad pattern of violation, with the top 10 percent of all drivers averaging 94 hours, including a 97 hour average for local drivers. At the median, only the local drivers stay below the 60 hour limit and regional drivers hit that limit exactly.

An important note on methodology is in order, however. We carefully asked drivers what work they performed by asking them how many hours they drove and how many hours they worked loading or unloading, waiting for freight (for a dispatch, to load, or to unload), and performing miscellaneous tasks such as mechanical repairs (or waiting for mechanical repairs) or waiting for bills to be cut. We did not want drivers to tell us what hours they logged and otherwise to make judgements on what constituted "work" because we believe drivers will tend to report only those hours claimed for purposes of pay. If they report only the latter, but in fact put in more hours unpaid, then the results will be biased downward. As indicated below, we found that drivers work a significant number of unpaid hours, contributing to potential underreporting problems.

Table 39: Hours in Last 7 Days

	Full Survey	Full Survey, Local	Full Survey, Regional	Full Survey, Long Haul
Mean	64.3	65.0	62.6	65.0
10th pct	36.0	44.0	38.0	33.0
25th pct	50.0	45.0	50.0	50.0
Median	62.0	58.0	60.0	65.0
75th pct	75.0	72.0	70.0	80.0
90th pct	94.0	97.0	80.0	96.0
	n=451	n=49	n=113	n=281

While this pattern of violation extends across all groups, as expected non-union drivers work an average of 11 percent more hours than do union drivers. The median union driver works 60 hours, while the non-union driver works 65 hours. The biggest problem comes at the highest level, as 10 percent of all union drivers exceed the legal limit by 20 hours while the top 10 percent of all non-union drivers exceed that limit by 40 hours — a full normal work week.

Table 40: Hours in Last 7 Days

	Full Survey, Ee Drivers: Union	Full Survey, Ee Drivers: Non-Union
mean	61.2	68.0
10th pct	33.0	42.0
25th pct	50.0	50.0
median	60.0	65.0
75th pct	70.0	80.0
90th pct	80.0	100.0
	n=46	n=287

We see the same pattern in the relationship between company drivers and owner-operators. Owner-operators stay closer to the legal limit while company drivers work substantially more than the allowable hours. Again, the sample we use for the regression models that appear later in this analysis includes only mileage-paid drivers, and their work hours exceed the legal limit substantially, both at the mean and at the median.

Table 41: Hours in Last 7 Days

	Full Survey, OTR Ees	Full Survey, OTR OOs
mean	67.2	56.5
10th pct	40.0	22.0
25th pct	50.0	40.0
median	65.0	60.0
75th pct	78.0	75.0
90th pct	96.0	80.0
	n=287	n=114

Table 42: Hours in Last 7 days

	Regression Sample, Mileage Paid Ees
mean	66.3
10th pct	42.0
25th pct	50.5
median	65.0
75th pct	75.0
90th pct	90.0
	n=201

We also have looked at the number of hours worked in the last 24 hours and in the last trip. We find that there is a direct, if modest, relationship between the number of hours worked per day and the length of trip taken by the driver. Long-haul drivers work the greatest number of hours; at the mean, long haul drivers work 12 percent more hours during any single day than do regional drivers, and 15 percent more hours on any single day than do local drivers. Not surprisingly, they also drive more of those hours and spend less of their time in any given day performing non-driving labor. At the mean, long-haul drivers perform non-driving work 23 percent of their time, while regional drivers work 25 percent of their time and local drivers perform non-driving work 37 percent of their time. Perhaps the most surprising figure is the percentage of non-driving labor for long-haul drivers. We think labor time is "lumpy" and long-haul drivers may spend a great deal of time loading or unloading, and fractionally their non-driving labor is high because this time tends to be lengthy and unpaid.

Perhaps most startling is the extent to which drivers are exceeding the daily hours-of-service rules. At the 75th percentile, long-haul drivers are working 15.5 hours, which scarcely allows the minimum 8 hour break along with a very limited half hour of break time within the 15 hour limit. At the 90th percentile long haul drivers work 19 hours, leaving only 5 in the last 25 for non-work activity. These figures lead us to believe that more than 25% of all long-haul drivers are in daily violation of HOS limits. In addition, figures of 12 hours of driving per day (75th percentile) along with 15 hours per day at the 90th percentile strongly suggests the pervasiveness of driving violations.[2]

Table 43: Hours Worked in the Last 24 Hours

	All	Local	Regional	Long Haul
obs	436	45	107	278
mean	11.35	10.38	10.63	11.93
10th pct	5.5	7	6	5
25th pct	8	8.25	8	8
median	11	10.25	10.5	11.5
75th pct	14	12	12.5	15.5
90th pct	18	16	16	19

[2] While averages sum up across all groups, each of these tables represents different distributions (total time, driving time, and non-driving work time. These distributions are not normal — the right tails are much thicker than the left tails — and they vary. For example, a driver who drives the mean number of hours (8.33) may have zero non-driving labor time or he may have five hours of non-driving labor time. The driver with 8.33 hours of driving and zero hours of non-driving labor would show up just above the median on the distribution of driving time but three hours below the median on total work time and below the 10th percentile on the distribution of non-driving labor time. Conversely, the driver with the mean number of driving hours but with five hours of labor would show up above the median on driving, between the 75th and 90th percentile on non-driving labor hours, and below the 75th percentile on total hours.

Table 44 Hours Driven in the Last 24 Hours

	All	Local	Regional	Long Haul
obs	436	45	107	278
mean	8.33	6.6	7.87	8.95
10th pct	3.5	1	3.5	3.5
25th pct	6	4.5	6	6
median	8	7	8	9
75th pct	10	8	10	12
90th pct	14	11	12	15

Table 45: Non-Driving Hours Worked in the Last 24 Hours

	All	Local	Regional	Long Haul
obs	436	45	107	278
mean	3.02	3.78	2.76	2.98
10th pct	0.25	1	0.5	0
25th pct	1	1.5	1	0.75
median	2	3	2.25	2
75th pct	4	5	4	4
90th pct	7	8	6	8

Table 46: Ratio Non-Driving Hours to Total Hours Worked

	All	Local	Regional	Long Haul
obs	436	45	107	278
mean	26%	37%	25%	23%
10th pct	3%	9%	6%	0%
25th pct	10%	20%	13%	8%
median	21%	33%	23%	17%
75th pct	35%	50%	33%	32%
90th pct	55%	67%	50%	56%

A great deal of efficiency is lost when drivers spend their labor time waiting. While arguably drivers are creating value when they are working (even though they may not be paid), loading or unloading a truck for example, they are not creating any value when they are waiting, as for a dispatch, to load, to unload, or for some other purpose. This inefficient use of their time is the source of a great deal of slack in the system. Since most drivers are not paid for this time, or earn a very small piece-work rate for activities, this waste of time is relatively costless to the economy (both to the shipper and the consignee, and generally to the trucking company) but represents an opportunity cost to the driver. The economic cost can more likely be measured in turnover and low human capital investment, as well as a tendency for drivers to pack in working (mainly driving) hours in addition to this wait time to make up for their lost earnings. The cost also likely can be found in a higher rate of fatigue-induced accidents, injuries, and occupational health disorders.

We see from our data that long-haul drivers put in the most work time per trip, though their trips are considerably longer than those of their local or regional counterparts. When we look at waiting time, however, we see a disproportionate waste of time on the part of long-haul drivers. The average driver waits more than twice as many hours as he works (non-driving labor), but the distribution is skewed. Local drivers wait somewhat less than they work (which makes sense since they usually are paid by the hour) but long haul drivers wait almost three times as long as they work; for long-haul drivers work time generally goes unpaid and waiting time almost always is unpaid.

Looking ahead to the section that calculates the cost of compliance with the current HOS rules, we can see that if less of these drivers' time was wasted, carriers would make more efficient use of skilled labor, and the cost to shippers, consignees, and the economy would be dramatically lower. Shippers and receivers do not consider the opportunity cost this wasted time imposes on drivers, much less the cost imposed on the economy. On the contrary, the current system imposes perverse incentives on those with the power to conserve this wasted resource: if it is more convenient to them to waste the resource (and if they do not pay for it), then they will do so. After all, the average long-haul driver wastes more than 6 hours per trip waiting around, and spends well over 8 hours in combined non-driving work time (technically line 4 on the driver's log). Realistically, the driver probably logs much of this wasted time as "off duty" and this explains his long average weekly hours.

Table 47: Total Hours Worked in the Last Trip

	All	Local	Regional	Long Haul
mean	22.48	8.33	13.82	29.58
10th pct	5.67	2.25	5	7.5
25th pct	9.33	5.58	7	13.5
median	14.5	7.67	10.25	20.5
75th pct	24	10.55	14	30.5
90th pct	40	13.89	20	50.38

Table 48: Waiting Time in the Last Trip (in minutes)

	All	Local	Regional	Long Haul
mean	282.94	73.71	196.68	371.97
10th pct	0	0	0	0
25th pct	15	0	0	30
median	90	30	60	120
75th pct	240	120	135	300
90th pct	600	173	360	900

Table 49: Working Time in the Last Trip (in minutes)

	All	Local	Regional	Long Haul
Mean	117.8	94.62	109.28	126.62
10th pct	0	15	0	0
25th pct	15	30	15	15
Median	60	60	45	60
75th pct	150	120	120	180
90th pct	270	200	210	290

Table 50: Waiting Time in the Last Trip as Percent of Total Non-Driving Time

	All	Local	Regional	Long Haul
Mean	71%	44%	64%	75%
10th pct		0%		
25th pct	50%	0%	0%	67%
median	60%	33%	57%	67%
75th pct	62%	50%	53%	63%
90th pct	69%	46%	63%	76%

The tables above show the extent to which drivers' time is spent doing tasks other than driving. We believe that when this time is unpaid, it probably contributes to excessive hours, as drivers log unpaid time off duty. To what extent is this a problem? The following tables show paid time as a percent of all non-driving time. We see that at the mean, 29 percent of all non-driving time is paid, but at the median the percentage of paid time is zero. This means that more than half of all drivers earn nothing for this labor. Looking further it becomes clear that most union drivers are paid for their time, as 72.7 percent of the union driver's time is paid at the median, while for non-union drivers, at the median their ratio of paid time to total non-driving time is zero percent. We see that at the 75th percentile 70.6 percent of the non-union driver's total non-driving time is paid, while the corresponding figure for union drivers is 100 percent. Note also that owner-operators have an even worse problem than do ordinary non-union drivers, as at the 90th percentile only 66.7 percent of their total non-driving time is paid.

Table 51: Paid Time as Percent of Total Non-Driving Time

	Full Survey	Full Survey, Local	Full Survey, Regional	Full Survey, Long Haul
mean	29.0%	50.4%	35.0%	22.1%
10th pct	0.0%	0.0%	0.0%	0.0%
25th pct	0.0%	0.0%	0.0%	0.0%
median	0.0%	40.0%	0.0%	0.0%
75th pct	70.0%	100.0%	98.0%	42.1%
90th pct	100.0%	100.0%	100.0%	100.0%
	n=312	n=29	n=78	n=201

Table 52: Paid Time as Percent of Total Non-Driving Time

	Full Survey, OTR Ees	Full Survey, OTR OOs
mean	31.6%	12.6%
10th pct	0.0%	0.0%
25th pct	0.0%	0.0%
median	0.0%	0.0%
75th pct	72.7%	0.0%
90th pct	100.0%	66.7%
	n=199	n=82

Table 53: Paid Time as Percent of Total Non-Driving Time

	Full Survey, EE Drivers: Union	Full Survey, EE Drivers: Non-Union
mean	57.4%	31.2%
10th pct	0.0%	0.0%
25th pct	0.0%	0.0%
median	72.7%	0.0%
75th pct	100.0%	70.6%
90th pct	100.0%	100.0%
	n=31	n=201

Table 54: Paid Time as Percent of Total Non-Driving Time

	Full Survey	Regression Sample, Mileage Pay
mean	29.0%	36.2%
10th pct	0.0%	0.0%
25th pct	0.0%	0.0%
median	0.0%	0.0%
75th pct	70.0%	88.9%
90th pct	100.0%	100.0%
	n=312	n=148

Earnings

We believe the wage and earning picture can tell us a great deal about why drivers work as hard as they do. While driver mean earnings looks pretty good for a somewhat skilled but generally not highly educated worker, one must recall the number of hours worked to achieve such earnings levels. While the mean driver earns more than $36,500 annually, he also works an average of about 3,300 hours per year to do it. This is more than half again as many hours as the full time standard year in the United States and considerably more than 50 percent more hours than the average employee actually works. With these earnings targets, it may not be surprising that we find excessive weekly labor.

The following table shows that long haul drivers make less than regional drivers. This is consistent with previous research that showed that the lowest paid drivers worked for long-haul TL carriers. That research showed that rates for drivers working for regional carriers averaged 31.0¢ per mile while those working for national carriers averaged 25.1¢ per mile. While the highest pay rate went to national LTL carriers (at 40.1¢ they could afford to abide by the law), at 22.7¢ the mileage rate for national TL drivers was 43% less and they were not paid for their non-driving labor (see Belzer, Michael H. 1995. "Collective Bargaining After Deregulation: Do the Teamsters Still Count?" *Industrial and Labor Relations Review* 48:636-655).

Table 55: Annual Wage

	Full Survey	Full Survey, Local	Full Survey, Regional	Full Survey, Long Haul
mean	$ 36,572	$ 37,237	$ 37,907	$ 35,945
10th pct	$ 19,000	$ 20,000	$ 22,000	$ 18,000
25th pct	$ 27,000	$ 26,000	$ 30,000	$ 25,235
median	$ 36,000	$ 40,000	$ 36,000	$ 35,000
75th pct	$ 46,000	$ 46,000	$ 48,000	$ 45,000
90th pct	$ 53,000	$ 53,000	$ 53,000	$ 53,000
	n=451	n=49	n=113	n=281

Owner-operators earn somewhat less than do company drivers, suggesting profits may be quite low (owner-operators often commingle these concepts). While median earnings are the same, mean earnings of owner-operators are about 5 percent lower than those of company drivers. Recall, of course, that owner operators drive fewer miles and work fewer hours, but their returns on their capital investment appear relatively low.

Table 56: Annual Wage

	Full Survey, OTR Ees	Full Survey, OTR OO
mean	$ 37,103	$ 35,244
10th pct	$ 22,000	$ 11,000
25th pct	$ 30,000	$ 23,000
median	$ 35,000	$ 35,000
75th pct	$ 45,000	$ 50,000
90th pct	$ 53,000	$ 59,000
	n=287	n=114

As previous research has shown, the most striking difference in driver wages comes from the influence of the union. Collective bargaining clearly provides union drivers with great advantages in comparison with their non-union counterparts. Articles by Belzer (Belzer, Michael H. 1995. "Collective Bargaining After Deregulation: Do the Teamsters Still Count?" *Industrial and Labor Relations Review* 48:636-655) and Hirsch (Hirsch, Barry T. 1993. "Trucking Deregulation and Labor Earnings: Is the Union Premium a Compensating Differential?" *Journal of Labor Economics* 11:279-301) show the union bargaining effect but also suggest that this union premium is also due to industry segment and human capital effects. Regardless of the cause, collective bargaining does appear to provide a "high road" with a nearly 26 percent earnings advantage over the non-union employees. Since non-union employees also work 8.3 percent more hours, the real advantage may be closer to 34.3 percent, not including the value of benefits (which also is considerably higher for unionized employees).

Table 57: Annual Wage

	Full Survey, Ee Drivers: Union	Full Survey, Ee Drivers: Non-Union
mean	$ 43,251	$ 35,933
10th pct	$ 22,000	$ 20,000
25th pct	$ 35,000	$ 28,000
median	$ 44,000	$ 35,000
75th pct	$ 52,500	$ 45,000
90th pct	$ 62,000	$ 52,000
	n=46	n=287

Finally, we present the regression sample here because it looks similar to that of the full sample, though somewhat higher. This excludes percentage-paid and hourly employees as well as owner-operators.

Table 58: Annual Wage

	Regression Sample, Mileage Pay
mean	$ 37,765
10th pct	$ 24,000
25th pct	$ 30,000
median	$ 37,000
75th pct	$ 46,000
90th pct	$ 53,000
	n=201

Pay System

What activities are drivers paid for? From the discussion above, it appears that drivers put in a lot of unpaid time. Indeed, the following table shows that fewer than a majority of all drivers are paid for non-driving labor. While most union drivers are paid for their time, at best most non-union drivers (mainly in the truckload sector) put in a quite a number of unpaid hours. While the data show that a relatively high proportion of drivers may get some compensation for long waits, most are not paid for routine delays, and many not even for routine labor.

One source of unpaid time was waiting for dispatch. Drivers often experience the transition from a delivery to a pickup as "frictional time;" a regular period of uncertainty during which they wait for an assignment. Many drivers, in the irregular long-haul TL industry, have to wait between loads while their company decides where to send them to make their next pick up. Owner-operators often spend many hours waiting for or locating a load. These frictional periods often are quite long and ordinarily neither owner operators nor company drivers are paid.

Table 59: Drivers Paid for Non-Driving Work

	All	Local	Regional	Long Haul
Waiting Tasks				
Dispatch	24%	39%	24%	21%
Loading / Unloading	30%	50%	34%	25%
Other	14%	16%	18%	12%
Working Tasks				
Loading / Unloading	43%	54%	48%	40%
Dropping / Hooking	22%	43%	16%	20%
Other	11%	15%	14%	9%

The above chart shows loading and unloading as both waiting and working because sometimes drivers wait while others load or unload their trucks. Other times they physically load or unload the trucks. In either case the drivers are on duty not driving because they must be responsible for loading operations or for their truck during this period. For example, if a driver stands on a dock and supervises the loading process as a warehouse worker loads pallets on his trailer, he is working. Likewise, if a driver stacks 40,000 pounds of freight in his trailer he is working, though much harder. The above data show that most drivers earn nothing for either form of labor.

How are drivers paid? Clearly most over-the-road drivers are paid on a contingent basis, that is, by the mile or by a percentage of the load revenue. The latter method is most common among owner-operators, who usually act as subcontractors for motor carriers. It also is common among non-union drivers, but is relatively uncommon for union drivers. In this early stage of analysis we also have developed a rather crude indicator of whether drivers are paid for non-driving time. We believe that to the extent they are not paid for non-driving time, they have an incentive to log this time as off duty to conserve their hours. We were surprised, however, to find so many "local" drivers paid by the mile. We suspect that many of these are the "home base" drivers described in the proposed HOS revision.

Table 60: Pay Structure

	Full Survey	Full Survey, Local	Full Survey, Regional	Full Survey, Long Haul
Paid for Any Non-Driving Time	60.2%	60.2%	67.1%	57.0%
Paid By Mile for Driving	58.4%	27.0%	51.4%	69.5%
Paid Percent of Revenue for Driving	35.5%	32.1%	43.9%	31.4%

Table 61: Pay Structure

	Full Survey, OTR Ees	Full Survey, OTR OO
Paid for Any Non-Driving Time	66.1%	45.4%
Paid By Mile for Driving	71.0%	42.5%
Paid Percent of Revenue for Driving	23.8%	66.6%

Table 62: Pay Structure

	Full Survey, EE Drivers: Union	Full Survey, EE Drivers: Non-Union
Paid for Any Non-Driving Time	83.7%	61.7%
Paid By Mile for Driving	56.3%	64.3%
Paid Percent of Revenue for Driving	17.8%	27.5%

Recall that in the regression models below, we have separated out mileage paid drivers for analysis, since those are the only ones for whom we have an accurate measure of the wage. We have tried to construct a generalized model of the wage, but have been unable to build such a construct in which we have confidence in the time allotted for this study. If we continue to do further analysis, we will try to build a useful wage model that works for all drivers.

Table 63: Pay Structure

	Full Survey	Regression Sample, Mileage Pay
Paid for Any Non-Driving Time	60.2%	74.3%
Paid By Mile for Driving	58.4%	100.0%
Paid Percent of Revenue for Driving	35.5%	0.0%

Night Driving

Our survey provided an interesting look at the extent of night driving among truck drivers. The survey asks drivers how many hours they worked between the hours of 11 PM and 7 AM, the shift known as the "graveyard shift." We were surprised to find that drivers reported a relatively small amount of night driving. At the mean drivers drove 29.0 percent of their time between those hours (Table 67), with local and long haul drivers putting in a somewhat smaller proportion of their time in night driving and regional drivers doing the most. For this quick research project we will not have time to analyze this data in depth, but it appears that drivers put in less night work than we thought.

The proposed HOS restriction involves cutting drivers' night driving (defined as between 12:00 AM and 6:00 AM) to 18 hours per week. First, we recall that the average driver works 64.3 hours weekly (Table 39), of which 26 percent (Table 46) is non-driving. Multiplying 64.3 by .74 we calculate that the average driver drives 47.6 hours per week. Based on the "last full trip" information, the average driver in our sample spends 29% of his or her driving time between the hours of 11:00 p.m. and 7:00 a.m. (the hours our survey asked about). If we assume a uniform distribution of reported night driving over this period, then we can estimate that the average driver would have 75 percent of his overall night driving hours in the policy-relevant six hours between midnight and 6 AM). We calculate that the average driver would be driving 21.75 percent of his time during the proscribed hours of the day (.75*.29). Using the sample mean driving total of 47.6 hours, this suggests the average driver currently drives 10.4 hours during the 12:00 AM to 6:00 AM period each week, well within the proscribed limits. From our data we have no way to tell which hours in the 11:00 p.m. to 7:00 a.m. period our respondent drivers used for the night driving they reported to us, but we believe if the uniform distribution assumption is false, it is because drivers were more likely to have been rolling between 11 PM and midnight and between 6:00 and 7:00 AM than between the midnight to 6:00 period. In fact, we ended up juggling our interview schedule eventually because we were unable to get enough drivers during the early morning hours to justify maintaining a shift of interviewers. The estimate of 10.4 hours, therefore, is conservative.

These calculations are based on the mean, however, so depending on the characteristics of those drivers exceeding the mean either in hours worked or percent of night driving, these characteristics might be different at the extremes. For example, in the LTL sector most of the regional carriers' drivers operate through the night, five days a week, but do so within the 60 hour weekly limit (by inference, much of the union work force in our sample). In the national LTL and in the package delivery sector, tractor trailers run throughout the night as well as during the day. The safety record of these carriers, however, generally is the best in the nation so it is not clear to us that we would see a safety benefit and the carriers would experience a major business dislocation if night time hours were cut dramatically.

Table 64: Night Percentage Last Trip

	Full Survey, Local	Full Survey, Regional	Full Survey, Long Haul
mean	27.3%	30.6%	28.4%
10th pct	0%	0%	0%
25th pct	0%	0%	0%
median	18%	27%	25%
75th pct	43%	50%	45%
90th pct	100%	88%	67%
	n=49	n=113	n=281

Table 65: Night Percentage Last Trip

	Full Survey, OTR Ees	Full Survey, OTR OO
mean	28.6%	30.1%
10th pct	0%	0%
25th pct	0%	0%
median	25%	25%
75th pct	48%	41%
90th pct	70%	82%
	n=287	n=114

Table 66: Night Percentage Last Trip

	Full Survey, Ee Drivers: Union	Full Survey, Ee Drivers: Non-Union
mean	32%	28%
10th pct	0%	0%
25th pct	0%	0%
median	30%	23%
75th pct	57%	48%
90th pct	67%	70%
	n=46	n=287

Table 67: Night Percentage Last Trip

	Full Survey	Regression Sample, Mileage Pay
mean	29.0%	28%
10th pct	0%	0%
25th pct	0%	0%
median	25%	24%
75th pct	47%	47%
90th pct	71%	67%
	n=451	n=201

The percent driven at night is defined as those hours driven between 11 PM and 7 AM. If we assume these are distributed uniformly, then the percent driven between midnight and 6am should comprise 75 percent of the reported number, which would result in the means and medians below.

Table 68: Estimated Night Percent

	Full Survey, Local	Full Survey, Regional	Full Survey, Long Haul
mean	20%	23%	21%
median	13%	20%	19%

Table 69: Estimated Night Percent

	Full Survey, OTR Ees	Full Survey, OTR OO
mean	21%	23%
median	19%	19%

Table 70: Estimated Night Percent

	Full Survey, EE Drivers: Union	Full Survey, EE Drivers: Non-Union
mean	24%	21%
median	23%	17%

Table 71: Estimated Night Percent

	Full Survey	Regression Sample, Mileage Pay
mean	21%	21%
median	19%	18%

The impact on the industry would be uneven, however, as we suggest in Section 1.3.3. The regional LTL industry depends almost entirely on these hours of driving, as overnight-delivery carriers' drivers operate their vehicles in regular schedules that typically span the entire policy-relevant night-time driving period. The national LTL industry depends significantly on these hours as well, though less so than does the regional LTL industry. Both of these industries are relatively heavily union (perhaps 50%) so that the higher percentage of night driving reflected in Table 68 probably reflects the industry effect. The long-haul and truckload industries depend the least on these hours, as drivers use their personal schedules more frequently. Other industries, such as those specializing in Just-In-Time deliveries, also use these night-time driving hours heavily.

Irregularity of Schedule: The extent and impact of backward rotation

The current proposed HOS revisions would limit backward rotation of schedules while putting no constraint on forward rotation. We have used two proxies for irregularity in this analysis to try to model this phenomenon. We did not collect the data originally with this specific analysis in mind, so these represent our best effort in a brief analysis to proxy irregularity.

The first irregularity variable is designed to capture whether a driver drives more than ten hours in twenty four, thus suggesting that he rotates his schedule backward as hours become available. Again, this assumes the driver is obeying the HOS rules currently (which most drivers do not). We would need more research to study the question in any greater depth. The definition of irregularity follows.

- Irreg1 is computed as a binary variable based on a ratio. The ratio is: in the denominator, the sum of elapsed trip time and time off immediately previous to the trip, and in the numerator, trip driving time. The variable is coded "1" if this ratio is greater than 10/24=.42.

- Irreg2 is computed as a binary variable based on a ratio. The ratio is: in the denominator, the sum of elapsed trip time and time off immediately previous to the trip, and in the numerator, trip working time ("working" includes waiting as well as direct labor). The variable is coded "1" if this ratio is greater than 12/24=.5.

Here's the intuition behind these two proxies. The seven-day-sixty-hour or eight-day-seventy-hour limit in the present regulations for total on-duty time (whether driving or not) gives drivers an incentive to log no more than ten hours work time per twenty-four hour day. This is because if you use more than this in a given day, and don't have a day later in the sliding seven or eight day period with little work to do, you will hit the total hours limit before the seventh or eighth day arrives. This means you will be stuck for a day while you sit and wait to pick up some hours dropping off the earlier end of the sliding period, raising the number of hours you can work today without violating the overall total limit.

Now drivers can legally log up to sixteen hours driving in a twenty-four hour period under the current regulations, if they aren't bumping up against the seven or eight day total hours limit by doing so. When they do, it represents "accelerating their tour-of-duty cycle". This enables them to get in more driving miles immediately, at the cost of knowing they will have to sit sometime later (if they are in fact complying with the regulations). The irreg1 variable is a binary variable that is one for those drivers who report having driven more than ten hours in the past twenty-four, and zero otherwise. So it represents a qualitative proxy for accelerating one's tour of duty cycle, which in turn is likely to involve starting at different times on succeeding days.

The irreg2 variable is a bit less useful. It is a binary variable that is one if a driver reports more than twelve total work hours in the last twenty-four, and zero otherwise. So if we assume that all work time is being logged, it represents a qualitative proxy for starting one's work at a later time on successive days. If this assumption is false (as we think likely), then it picks out those drivers who would be negatively impacted by a twelve hour work limit in a twenty-four hour period, assuming that they fully comply with a new regulation imposing this limit.

We find that irregularity is somewhat negatively related to the driving time, as we find that at both the mean and the median, drivers whose schedules are regular use a greater proportion of their time driving.

Table 72: Percent Driving on Last Trip

All	irreg1=1	irreg1=0	irreg2=1	irreg2=0
mean	71%	72%	61%	78%
10th pct	36%	41%	29%	50%
25th pct	57%	59%	46%	67%
median	76%	75%	62%	80%
75th pct	90%	88%	77%	91%
90th pct	96%	95%	90%	97%

Table 73: Percent Driving on Last Trip

Mileage Drivers	irreg1=1	irreg1=0	irreg2=1	irreg2=0
mean	71%	76%	62%	80%
10th pct	28%	51%	28%	62%
25th pct	62%	67%	48%	72%
median	74%	79%	65%	81%
75th pct	89%	91%	78%	91%
90th pct	96%	96%	90%	96%

Most striking, we find a strong relationship between irregularity (however proxied) and the percent of waiting time on the last trip. This suggests that drivers who have a lot of down time are more likely to engage in risky behaviors like turning their biological clock back to deliver the freight or get more hours. We might infer from this that waiting time wastes the driver's time, and forces or encourages him to adopt a more irregular schedule.

Table 74: Percent Waiting Time on Last Trip

All	irreg1=1	irreg1=0	irreg2=1	irreg2=0
mean	19.5%	16.9%	26.3%	12.6%
10th pct	0.0%	0.0%	0.0%	0.0%
25th pct	2.7%	1.5%	7.3%	0.7%
median	15.1%	10.4%	20.0%	7.7%
75th pct	25.2%	24.2%	42.9%	19.4%
90th pct	53.1%	44.4%	61.4%	33.0%

Table 75: Percent Waiting Time on Last Trip

Mileage Drivers	irregl=1	irregl=0	irreg2=1	irreg2=0
mean	18.8%	13.8%	23.6%	11.7%
10th pct	0.1%	0.0%	0.1%	0.0%
25th pct	3.6%	1.5%	7.1%	1.5%
median	14.8%	8.6%	16.3%	7.1%
75th pct	22.1%	20.0%	32.1%	16.7%
90th pct	53.1%	33.3%	53.1%	31.7%

We observe mixed results looking at the relationship between annual miles driven and irregularity. For our whole survey, the differences between those who have regular and irregular schedules are modest, with very nearly the same miles reported on average by both groups. We observe, however, that at the median drivers with irregular schedules drive modestly more miles than do regular drivers, though the averages are very nearly identical. For mileage paid drivers, however, the relationship is stronger and in the opposite direction. That is, at the mean regular drivers (irregl) cover about 8% more miles, which mainly can be seen at high mileage levels. For those fitting the irreg2 definition, the averages are extremely close and irregular drivers at higher mileage get more miles than their more regular counterparts. The variable "irregl" is used in the regression equations in Section 1.3.2, and is a robust predictor.

Table 76: Annual Miles and Irregular Schedule

Full Survey	irregl=1	irregl=0	irreg2=1	irreg2=0
obs	112	339	164	287
mean	113,840	112,430	112,673	112,816
10th pct	50,000	60,000	50,000	60,000
25th pct	100,000	90,000	80,000	100,000
median	120,000	110,000	113,000	110,000
75th pct	137,000	130,000	137,000	130,000
90th pct	160,000	160,000	165,000	150,000

Table 77: Annual Miles and Irregular Schedule

Mileage Drivers	irregl=1	irregl=0	irreg2=1	irreg2=0
obs	35	166	53	148
mean	114,598	123,007	121,827	121,472
10th pct	50,000	80,000	50,000	80,000
25th pct	100,000	100,000	100,000	100,000
median	120,000	120,000	125,000	120,000
75th pct	145,000	140,000	150,000	140,000
90th pct	160,000	175,000	175,000	165,000

Observed as a product of weekly hours, however, we get a very different and more consistent story. Irregular drivers put in substantially more hours at the mean, at the median, and in most of the quintiles. The relationship is even stronger for mileage drivers, the regression sample. For this reason, regression will reveal a strong relationship to hours worked, controlling for other factors. Table 76 shows that irregularity is associated with dramatically higher mean and median hours and 90 percent of all irregular drivers (definition 1) work at least 126 hours or more.

Table 78: Irregularity and Weekly Hours

All	irreg1=1	irreg1=0	irreg2=1	irreg2=0
obs	112	339	164	287
mean	67	63.5	67.26	62.72
10th pct	38	36	36	38
25th pct	48	50	50	50
median	65	60	65	60
75th pct	80	70	80	70
90th pct	100	90	100	90

Table 79: Irregularity and Weekly Hours

Mileage Drivers	irreg1=1	irreg1=0	irreg2=1	irreg2=0
obs	35	166	53	148
mean	78.33	63.83	73.27	64.02
10th pct	48	42	45	42
25th pct	57.5	50	55	50.5
median	75	62	66	62
75th pct	80	70	80	70
90th pct	126	90	110	90

Do these excessive hours affect safety? Our survey had a limited number of questions that reflect safety (though our 1998-1999 survey has more), but for the questions we do have the effect is overwhelming. Irregularity generally is associated with a 50 percent higher likelihood that the driver will admit to violating the HOS regulations during the past 30 days (a question designed to repeat that of the Insurance Institute for Highway Safety in their survey reported in (Braver, Elisa R., Carol W. Preusser, David F. Preusser, Herbert M. Baum, Richard Beilock, and Robert Ulmer. 1992. "Who Violates Work Hour Rules? A Survey of Tractor-Trailer Drivers." . Arlington, VA: Insurance Institute for Highway Safety). We also asked drivers whether they had either one or more accidents or violations on their record over the past 12 months, and we likewise get a strong positive correlation between these safety proxies and irregularity. We do not find a particularly consistent relationship between admitted drowsy driving or falling asleep at the wheel, but there does seem to be a relationship between "irreg2" (the 12-hour model) and drowsiness. Note also that drivers who are paid for their non-driving time are significantly less likely to have irregular schedules.

Table 80: Irregularity and Safety

All Drivers	irreg1=1	irreg1=0	irreg2=1	irreg2=0
paid for any non-driving time	47.02%	64.25%	48.35%	66.71%
asleep or drowsy at wheel	20.32%	24.74%	26.69%	22.03%
unclean driving record	52.73%	36.49%	43.64%	38.51%
violate HOS in last 30 days	70.75%	52.94%	66.56%	51.74%

Table 81: Irregularity and Safety

Mileage Drivers	irreg1=1	irreg1=0	irreg2=1	irreg2=0
paid for any non-driving time	66.58%	75.88%	66.83%	76.75%
asleep or drowsy at wheel	25.93%	26.6%	29.72%	25.41%
unclean driving record	44.91%	33.58%	36.44%	35.23%
violate HOS in last 30 days	74.90%	50.75%	72.75%	48.79%

Finally, it appears that irregular driving is most associated with long-haul drivers and owner-operators. Note that while 13.1 percent of our sample were union members they were disproportionately distributed among local and regional drivers and less likely in long haul, with very few union owner operators. Irregular driving schedules were disproportionately concentrated among long haul drivers and especially owner-operators.

In Table 83 below note the relatively strong correlation between hours per week and irregularity, along with the correlation between drowsy driving and hours, miles, unclean driving record, and likelihood of working more hours than reported. Correlation among many of the variables are entirely consistent with over work. In Table 84 below note the extremely strong correlation between hours per week and irregularity, along with consistently strong correlation's between reported log violation and almost all safety-related variables of interest.

Table 82: Irregularity and Union Status

	Full Survey	*Regression Sample, Mileage Pay*	*Full Survey, Local*	*Full Survey, Regional*	*Full Survey, Long Haul*	*Full Survey, OTR Ees*	*Full Survey, OTR OO*	*Full Survey, Ee Drivers: Union*	*Full Survey, Ee Drivers: Non-Union*
union member	13.1%	14.2%	18.0%	19.2%	9.5%	16.1%	2.5%		
irregular driving	23.7%	17.2%	15.8%	19.9%	27.6%	16.6%	47.7%	18.0%	15.3%

Table 83: Irregularity Correlation for All Drivers

	irreg1	irreg2	drowsy	hrsweek	miles	unclean	report	bymile	percent
irreg1	1								
irreg2	0.6573	1							
drowsy	-0.0224	0.0534	1						
hrsweek	0.0806	0.106	0.0769	1					
miles	0.0183	0.0076	0.1121	0.1073	1				
unclean	0.1405	0.01	0.0997	0.0249	0.0681	1			
report	0.1366	0.122	0.2404	0.2735	0.2487	0.1212	1		
bymile	-0.0188	-0.1249	-0.0292	0.0647	0.1655	-0.113	-0.0314	1	
percent	0.1394	0.1588	0.0555	-0.076	-0.0263	0.1444	0.1179	-0.7	1

Table 84: Irregularity Correlation for Mileage Drivers

	irreg1	irreg2	drowsy	hrsweek	miles	unclean	report
irreg1	1						
irreg2	0.7049	1					
drowsy	0.0533	0.1005	1				
hrsweek	0.2497	0.1658	0.0796	1			
miles	-0.0369	0.0698	0.0988	0.0751	1		
unclean	0.0161	-0.0715	0.0494	0.0213	-0.1562	1	
report	0.1412	0.1651	0.2258	0.375	0.3486	0.07	1

Indicators

miles: annual miles

hrsweek: hours worked in the last 7 days

actmrate: actual mileage rate for this trip (only reported for drivers paid by the mile).

perwork: percent of total time on last trip spent on non-driving working activities.

perwait: percent of total time on last trip spent on waiting activities.

nightper: percent of time driven at night on last trip.

pdwork: whether the driver is paid in any way for any non-driving work.

pdwait: whether the driver is paid in any way for any waiting time.

drowsy: whether the driver reported drowsiness or falling asleep at the wheel at all in the last 30 days.

unclean: whether the driver reported an accident or moving violation in the last year.

report: whether the driver worked more than logged in the last 30 days.

1.3.2: Driver Impact.

Analysis will proceed from two baselines. We will look at proposed changes assuming perfect enforcement, and we will look at the changes and compare them with the actual status quo. With more than half of all drivers in violation of current regulations, not only do we need to calculate the impact of a change, but we need to calculate the potential impact of enforcing current rules. The driver survey, along with public employment data, will help us to estimate the cost of regulatory enforcement, or regulatory change, and the potential impact on employment. Using public and UMTIP driver survey data we will estimate the impact on driver earnings. We will attempt to analyze the potential benefit in terms of driver health, although data sources are uncertain.

First, we will analyze the nature of proposed changes and the likely affects on driver practices, assuming the regulations were obeyed. For this part of the analysis we will need to assume enforcement is efficient and cost-effective. We will perform a thought exercise, using our institutional knowledge of industry operations, to work out possible scenarios for drivers hours under various conditions. Second, we will look at proposed changes in light of current practice, as revealed by the driver survey. Will driver hours be reduced as a result? If so, what impact will that have on driver earnings? How are drivers likely to respond to this change?

Part I: Estimating the Number and Cost of Additional Truck Drivers Needed If the Existing Hours of Service Regulations Were Enforced

As part of the analysis of the impact of changing the Hours of Service (HOS) regulations, we have estimated the number of additional truck drivers that would be needed if all present drivers were required to limit their work time to 60 hours a week. We have also estimated the additional cost to the trucking industry of enforcing this restriction.

We have focused on regional and long-distance drivers because we believe that the primary focus of the HOS regulations is on regional and long-haul drivers, and because data on local drivers is scanty. With a longer lead time we could extend this analysis to local drivers, but we believe our analysis is applicable to this group. The UMTIP Driver Survey data suggest local drivers also exceed HOS regulations, though we suspect we have under-sampled local drivers due to our sampling frame of truck stops. Local drivers are less likely to stop at truck stops, and those who do may differ systematically with those who do not. Consequently, this analysis of the impact of enforcing HOS regulations would fall predominantly on regional and long-distance truckers. In deriving our estimates, we have made a few additional simplifying assumptions: (1) that there is perfect compliance of the new regulations, (2) that none of the present drivers quit the profession as a result of the new regulations, and (3) that the drivers are paid for 52 weeks per year. We are not including cost of enforcement itself in this analysis.

In order to estimate the number of additional truck drivers that would be required if the HOS 60-hours-a-week regulation were enforced, we need estimates of the number of regional and long-distance drivers. Unfortunately, the Trucking Industry Use Survey (TIUS) collects information only on distance traveled by vehicle, not by driver. Using information from the 1992 TIUS, the FHWA Office of Motor Carriers estimates that there were 482,442 trucks used in long-distance driving and 416,499 trucks used for regional driving. We estimate that there are about 300,000 owner-operators. If we assume that each owner-operator has only one truck and that all drivers are either regional or long-distance drivers, then there are 598,941 (482,442 + 416,499 – 300,000) regional and long-distance for-hire trucks in the United States. According to the ATA/ICC/BTS Form M data set, regional and long-distance trucking companies employ 9.45 percent more drivers than trucks. Therefore, we estimate that the total number of regional and long-distance drivers in the United States is 955,541 $\{300{,}000 + (1.0945 \times 598{,}941)\}$. If we assume that drivers are distributed in the same proportion as trucks, then there are 442,723 regional and 512,818 long-distance drivers in the United States.

According to the University of Michigan's 1997 survey of truck drivers (UMTIP Driver Survey), 54 percent of regional drivers and 53 percent of long-distance drivers work over 60 hours a week. Multiplying these values by the estimated number of regional and long-distance drivers produces estimates that 239,070 ($0.54 \times 442{,}723$) regional and 271,794 ($0.53 \times 512{,}818$) long-distance drivers typically work over 60 hours a week. According to the UMTIP Driver Survey, the typical regional driver working over 60 hours a week works 70 hours a week, or 10 hours a week more than the HOS regulations allow. The typical long-distance driver working over 60 hours a week actually works 80 hours a week, or 20 hours a week more than the HOS regulations allow. Consequently, regional drivers, in aggregate, currently exceed the HOS regulations by 2,390,700 ($239{,}070 \times 10$) hours a week, and long-distance drivers exceed the HOS regulations by 5,435,880 ($271{,}794 \times 20$) hours a week (totaling 7,826,580 hours).

If drivers were prohibited from working the nearly 8,000,000 extra hours a week, the trucking industry would need to do one of the following: (1) increase the hours of drivers currently working fewer than 60 hours a week, (2) hire new drivers, or (3) significantly increase truck driver productivity by substantially reducing non-driving labor time. These alternative strategies will be examined in turn.

Forty-six percent of regional drivers (203,653), and 47 percent of long-distance drivers (241,024) work fewer than 60 hours a week. For these drivers (both regional and long-distance), the median number of hours worked per week is 50. If *all* of the drivers working at less than the maximum number of hours were to increase their work time to 60 hours a week, the industry could gain 4,446,770 hours per week $\{(60 - 50) \times (203{,}653 + 241{,}024)\}$. The industry would still need to hire new workers to make up the 3,379,810 hours (7,826,580 – 4,446,770) that would be taken away if all the present drivers were to work 60 hours a week. If all of the newly hired drivers worked 60 hours a week, the industry would still need 56,330 new regional and long-distance drivers (3,379,810 hours $\div$ 60 hours per driver), or 5.9 percent (56,330 $\div$ 955,541 total present drivers).

At the other extreme, if *all* present drivers working fewer than 60 hours a week were unable or unwilling to increase their hours, then the industry would need 130,443 (7,826,580 $\div$ 60) new drivers working 60 hours a week. This would represent a 13.7 percent increase in the present workforce of regional and long-distance drivers (130,443 ÷ 955,541 total present drivers). How much would this change cost the industry? The answer depends on two factors: (1) how much the earnings of present workers change as they vary their hours, and (2) how much the wage needs to change to attract a sufficient number of new workers into the industry.

The earnings profile of drivers in the trucking industry clearly shows that average annual (or weekly) earnings increase, but at a decreasing rate, as the average weekly hours increase. Truck drivers are not covered by the 40-hour limit provision of the Fair Labor Standards Act, which mandates time-and-a-half pay for hours over 40 hours a week, so earnings by drivers for hours beyond 40 hours a week depend on how that time is spent. If drivers spend that time driving, the primary method of compensation in the industry is by the mile driven, in which case earnings should increase proportionately to hours worked. If the additional hours result from non-driving labor time, which is frequently uncompensated or compensated at a relatively low rate, then earnings would increase by a smaller percentage than hours worked.

According to the regression results shown in Table 85, average annual earnings for drivers in the trucking industry increase by $364 ($7.01 an hour) for every additional hour worked between 35 and 59 hours a week, and by $322 ($6.20 an hour) for every additional hour worked over 59 hours a week. We suspect the observed declining hourly wage in trucking is due to the increased prevalence of bad jobs among drivers working more than the legal limit; they earn lower wages at all levels of hourly output. The results were estimated from an ordinary least squares regression of data on earnings and hours in 1997 from the March 1998 Current Population Survey. The sample consisted of all those who reported that truck driving was their "longest" occupation, that the trucking industry was their "longest" industry, and that they worked at least 35 hours a week for 50-52 weeks in 1997. Seven observations were dropped from the sample because the respondents reported that they had either negative or unbelievably high earnings (over $75 an hour). Also, one observation was dropped because the respondent was coded as a government employee working in the trucking industry. Dropping these observations did not significantly change the coefficients on the hours variables.

The estimates from the regression equation indicate that the typical driver in the trucking industry working 40 hours a week would earn $30,976 per year, a 60-hour-a-week driver would earn $35,737, and a 70-hour-a-week driver $38,959 per year.[3] These earnings levels calculated with the CPS compare favorably with those collected directly from drivers with the UMTIP Driver Survey, providing cross-validation between sets. The UMTIP Driver Survey shows that the average driver earns $36,752 and the average work week is 64.3 hours. The mean earnings for all drivers in the sample were $33,824, and the median earnings were $31,000.

[3] The predicted earnings values were calculated by assuming that all of the dummy variables in the equation assumed their mean values.

The interpretation of the coefficient on the variable measuring weekly hours for those working more than 60 hours a week is that for every hour worked over 60, the aggregate earnings of drivers, and correspondingly the aggregate cost to trucking companies, would be reduced by \$6.20 an hour. As mentioned earlier, aggregate hours of drivers working over 60 hours a week would be reduced by 7,826,580 hours per week if the HOS regulations were enforced. Consequently, the trucking industry would save \$48,524,796 per week (7,826,580 × \$6.20) in pay to truckers currently working over 60 hours a week. On the other hand, trucking industry payments to present workers who increased their hours to 60 a week, along with payments to the newly hired workers, would increase the costs to the trucking industry. All of the calculations of the costs to the trucking industry of enforcing 60-hour-a-week HOS regulations, for each of the scenarios considered here, are shown in Table 86.

The least expensive solution for the trucking industry would be for the present drivers working fewer than 60 hours a week to increase their effort to 60 hours a week. The coefficient on the variable measuring weekly hours for those working 60 or fewer hours a week means that for every hour under 61, the aggregate earnings of drivers, and correspondingly the aggregate cost to trucking companies, would be increased by \$7.01 an hour. These additional hours (4,446,770) would cost the trucking industry \$31,171,858 (\$7.01 × 4,446,770) per week, but the trucking industry would still need to hire 56,330 new workers. If the present truckers working fewer than 60 hours a week were unable or unwilling to increase their hours, the industry would need to hire 130,443 new workers. The cost of hiring these new workers depends on the elasticity of labor supply to the trucking industry.

Since there are no observable data on potential new entrants, their elasticity of labor supply cannot be estimated directly. Two considerations suggest that the responsiveness of labor supply to wages for this group is relatively elastic: (1) the barriers to entry for working in the industry are fairly low, and (2) historical data suggest that employment growth in the industry has not been significantly impeded by wage movements. Since a point estimate is not possible, we consider two boundary conditions for our calculations, which bracket the range of relatively elastic responses of labor supply to wages: (1) perfectly elastic labor supply, and (2) unitary elasticity of labor supply. Explanations of these two scenarios follow, with accompanying calculations summarized in Table 86.

If we assume that the regional and long-distance trucking industry can find the desired number of workers at the current wage rate (that is, assuming a perfectly elastic labor supply curve), then the cost of hiring the new workers (at 60 hours a week) would be \$38,712,793 ((\$35,737 ÷ 52) × 56,330) per week if the present workers increased their hours, and \$89,646,952 (\$35,737 ÷ 52) × 130,443) per week if they were either unable or unwilling to increase their hours. Consequently, the net labor cost to the trucking industry, even if we assume a perfectly elastic labor supply curve, would be between \$21,359,855 per week (\$1,110,712,460 annually) and \$41,122,156 per week (\$2,138,352,112 annually), depending on the ability and willingness of present workers to increase their hours.

If we assume that the labor supply elasticity is equal to 1.0 (unitary elasticity), so that any given percentage increase in the labor supply of new workers requires an equal percentage increase in the wage rate, the cost to the trucking industry of enforcing the HOS regulations increases dramatically. If present truckers were able and willing to increase their hours, then the average annual wage for a 60-hour-a-week driver would need to increase by 5.9 percent, or from $35,737 to $37,845. The higher wage paid to both present and new workers would cost the trucking industry an *additional* $2,133,024,068 per year {(955,541 + 56,330) × ($37,845 – $35,737)}. If present workers were unable or unwilling to increase their hours, then the wage rate would need to increase by 13.7 percent, or from $35,737 to $40,633. This higher wage rate would cost the trucking industry an *additional* $5,316,977,664 per year {(955,541 + 130,443) × ($40,633 – $35,737)}. Combined with the base cost described earlier, this means that the trucking industry's labor costs would increase by between $3.2 billion ($1,110,712,460 + 2,133,024,068) and $7.5 billion ($2,138,352,112 + $5,316,977,664) per year if the labor supply elasticity were 1.0.

The wages indicated in the preceding calculation use the driver census numbers from the CPS along with the driver earnings and wage figures developed in the UMTIP driver survey. We use the UMTIP driver survey rather than CPS in this analysis because it more closely approximates the wages earned by drivers holding the CDL and operating in interstate commerce. Overall driver wages are not calculated using the CPS and the marginal effect on driver wages ($7.01 between 35 and 59 hours, inclusive, and $6.20 greater than 59 hours) controls for firm size only (note that drivers for very small firms earn significantly less wages than the mean and drivers for very large firms earn significantly greater wages than the mean.

Clearly, labor cost increases of this magnitude would threaten the viability of many firms in the trucking industry (even the best-case scenario would result in an increase in total labor costs of $1.1 billion per year). Faced with such a change in its labor cost structure, the trucking industry would be forced to seek additional labor productivity improvements. One possibility would be to reduce non-driving labor time and correspondingly increase driving time.

According to the UMTIP Driver Survey, about three-quarters of total labor time is spent driving and the other quarter is non-driving labor time. Applying this ratio to the scenario where all present drivers work 60 hours a week, about 45 hours a week would be spent driving and 15 hours would be devoted to non-driving labor time. In this scenario, if non-driving labor time were cut by 25 percent with driving time increased correspondingly, we estimate that the trucking industry could meet the HOS 60-hour-a-week regulation without hiring any new drivers. Given the method of compensation in the industry, this would increase labor costs, but by a smaller amount than the alternatives outlined in Table 86.

Table 85: Estimating the Relationship between Annual Earnings and Weekly Hours for Truck Drivers in the Trucking Industry

	Regression results				Variable statistics	
Variable	Coefficient	Standard error	t ratio	Probability	Mean	Standard deviation
Intercept	16449	6177	2.663	0.008	N/A.	N/A.
Female	-13643	4925	-2.77	0.006	0.0232	0.1507
Self-employed	-956	2591	-0.369	0.712	0.1702	0.3762
Firm < 10	-7670	3051	-2.514	0.0122	0.0948	0.2932
Firm 10 to 24	-5340	3334	-1.604	0.1098	0.0716	0.258
Firm 25 to 99	-3740	2639	-1.417	0.1571	0.1586	0.3657
Firm 500 to 999	4827	3749	1.288	0.1985	0.0522	0.2227
Firm 1000 or more	6329	2317	2.731	0.0065	0.2979	0.4578
Hours < 60	364.31	132	2.76	0.006	34.3	19.1
Hours 60 or more	322.21	87.7	3.673	0.0003	15.2	28.7
Degrees of freedom	507					
R-squared	0.1217					

Table 86: Calculating the Cost to the Trucking Industry of Enforcing 60-hour-a-week HOS Regulations

	New labor supply is infinitely elastic		New labor supply elasticity equals 1.0	
	Increase existing hours	No increase in existing hours	Increase existing hours	No increase in existing hours
Savings from cutting hours	-$48,524,761	-$48,524,761	-$48,524,761	-$48,524,761
Expense for increasing hours	$31,171,858	$0	$31,171,858	$0
Expense for additional drivers	$38,712,841	$89,646,886	$38,712,841	$89,646,886
Higher wage cost for new labor supply	$0	$0	$41,029,092	$102,248,923
Weekly cost	$21,359,939	$41,122,126	$62,389,031	$143,371,049
Annual cost	$1,110,716,806	$2,138,350,541	$3,244,229,607	$7,455,294,539

Part II: Driver Survey-Based Econometric Modeling Results

Introduction. Our task is to estimate first, the social costs, and second, the effects on trucking industry participants, of potential changes in the HOS regulations for commercial motor vehicle operators. In this first attack on the problem we have attempted to construct a prototype methodology for generating such estimates. The prototype we have developed makes use of the unique survey data on truck drivers collected by the University of Michigan Trucking Industry Program, and while it is relatively primitive and *ad hoc* in its present form, it is potentially capable of validation, extension, and refinement in several ways (see Section VI).

In developing our prototype methodology we have considered only two specific versions of the potential HOS changes. These give us a reasonable initial idea of the magnitudes of the effects involved in the proposals being reviewed. Specifically, we consider (1) the effect of limiting night driving between the hours of 12:00 midnight and 6:00 a.m. to eighteen hours per work week, versus the current system of no limits. And, we consider (2) a simple version of imposing more schedule regularity on all drivers, in particular, the prohibition of more than one ten hour driving shift per twenty four hour period, versus the current system which permits more than one tour of duty per twenty four hour day (due to the fact that a new tour can begin after only an eight hour break, permitting starting times to "rotate backward"). Note that our method compares the current *status quo* (which involves considerable violations of the present rules) to perfect compliance with the new policy, and does not estimate any increase in enforcement costs that might be required to achieve this state. Nor does it adjust the social costs in any way to attempt to reflect potential levels of noncompliance.

In order to consider these potential changes using the UMTIP driver survey data, we take the information collected about the last complete trip cycle that each respondent driver completed, and construct variables for the percent of driving time performed at night (used for (1)), and whether or not the drivers is putting in more than ten hours of driving per twenty-four hour period (used for (2)). We take these variables as proxies for the relevant measures over all of a driver's work, thus implicitly assuming that the last trip cycle was representative of all the driver's work.

Our technique involves estimating a recursive econometric equation system on a subset of the first wave of the UMTIP Driver Survey data to provide two results, one for each equation. The first equation, in which the reported wage rate is the dependent variable, provides a direct estimate of the marginal social costs of imposing the two policy change versions mentioned above. Utilizing some simplifying assumptions spelled out below, we measure these costs directly, by using our estimated regression coefficients on the relevant proxy variables to simulate changes in the equilibrium pay rates of truck drivers due to (1) or (2). These changes are in turn assumed to affect the cost structure of the providers of trucking services, the rates they charge, and the ultimate costs for those services that are passed on to consumers. Under some further simplifying assumptions, we use these estimates of the marginal social cost to compute estimates of the total social costs of policy changes (1) and (2). A limitation to the present version of these estimates is that while the interpretation we give our econometric results are theoretically reasonably well supported, given our assumptions, the estimated coefficients are statistically somewhat imprecise, especially for policy change (1).

The second equation, in which the hours of work time reported to have been supplied in the last week is the dependent variable, and the predicted wage from the first equation is an explanatory variable, provides a result that is theoretically less well supported, and on which we place less reliance at present. It is an estimate of the increase in the number of hours of work per week effectively supplied by incumbent drivers who currently have irregular schedules. Using this estimated coefficient to simulate the change (reduction) in hours supplied per currently irregular driver due to policy change (1), and under further simplifying assumptions and using information on the marginal cost to firms of an hour of labor computed from CPS data in another part of the present study, we compute a second estimate of the total social cost of (1), the elimination of "schedule irregularity". This estimate is approximately twice that obtained through the first method, and we report it primarily for comparison, as we have less confidence in it. (The results of the second equation do not provide a usable estimate of changes in hours associated with the other potential policy change (2), limits on night driving.)

Measuring Marginal Social Cost. For a subset of the driver survey respondents consisting of the mileage paid employee drivers, we estimate a wage equation designed to explain the nominal mileage rate received by each respondent in terms of a set of appropriate independent variables. In this equation the coefficients estimated for the two policy-relevant factors (1) and (2) show negative values; that is, other things equal, being irregular or driving at night is associated with lower nominal mileage pay received. Under some assumptions stated below, we interpret this reduction in the wage rate as an estimate of the marginal per-mile benefit realized by society under the current level of these two operational characteristics.

The basic intuition behind this interpretation is as follows. Road drivers can be treated, to a first approximation, as if they only switch jobs based on how much they make in a week, once they are away from home. They work in a competitive labor market, if adjustments are made for union membership, and so their individual human capital characteristics essentially determine their next best job option, and hence the level of weekly wage they command. This is because, in competitive equilibrium, they can expect to make neither more nor less than the value to them of the hometime/weekly wage bundle that their fallback option would give them. So, a firm whose freight gives mileage-paid drivers more miles per week, either due to schedules that require a high proportion of night time driving, or due to schedule irregularity from "tour-of-duty acceleration," or due simply to excessive or intensified work (the sweating of labor), can on average pay a bit less per mile and still offer the weekly earnings level needed to just keep the marginal driver indifferent between working and quitting. But in a competitive freight market, this decrease will be reflected in freight rates, which are passed on ultimately to consumers. Hence, this decrease represents the marginal (i.e. per mile) social gain of such night driving or irregularity: the marginal cost contribution of truck transportation in the supply chain leading to consumer products is less by this amount.

This estimate is only for drivers in this subset of the commercial vehicle operator population, a limitation imposed by the problem of measuring nominal mileage rates for drivers paid by other methods (e.g. percentage of revenue). However, for a first approximation we assume that the estimate obtained for mileage-paid road drivers is representative of that for all road drivers, and use this to approximate the total social cost involved in the policy change of setting "irregularity" to zero and limiting night driving. Here are the assumptions under which the nominal wage equation may be properly interpreted to give estimates of the marginal social benefit of present policies.

(1) It is assumed that motor freight is an effectively competitive industry. Hence, the rates it charges approximately represent the marginal cost of providing trucking services.

(2) Road drivers don't care a lot about leisure consumed away from home, and so they don't have a standard labor-leisure tradeoff. While away from home they tend to work as many hours as will continue to increase their earnings by any positive amount, up to the limits defined by freight schedules and/or regulations. This is the most nonstandard of our assumptions, but we argue, based on our industry background, that it is plausible for road drivers. (We suggest in Section VI that this assumption might be tested in future work.)

(3) The labor market for commercial truck drivers is approximately in long term competitive equilibrium. That is, once we have accounted for differences in human capital and any other factors that explain differences in next best opportunities to the present job, drivers receive their reservation earnings and amenities bundle. So, once they go on the road, drivers bring home a weekly earnings package that makes them approximately indifferent between working on the schedule required on the road, and taking their next best job elsewhere.

(4) The level of night driving, and of irregularity in schedule caused by accelerating one's tour of duty cycle to a more rapid pace than one driving shift every twenty-four hours are, to a first approximation, due to the demands of the market for freight services. That is, shipper loading schedules and delays, consignee delivery windows and queues, and the like, are primarily responsible for driver schedule irregularity and night driving (and hence the levels of these that we observe are predominantly exogenous, as opposed to being significantly due to endogenous driver choices).

None of these assumptions is literally completely true, but all four are defensible as approximate descriptions of the market for regional and long haul truckload (TL) motor freight services, and the associated labor markets for drivers. The less-then-truckload (LTL) segment, and probably local trucking services, differ primarily in that employees tend to receive significant employment rents (especially in LTL); the other three assumptions are relatively reasonable even in these parts of trucking. When these four assumptions are satisfied, then the following story is sensible.

Freight that requires accelerated tour of duty schedules and night driving is associated with drivers running more miles (or having hours of paid non-driving work, if applicable) per week, which increases weekly earnings. Thus, firms on average are able to pay drivers working this type of schedule less per mile, other things equal, without lowering their weekly earnings. (Think of irregularity as producing a kind of an "employment rent", which firms tax away from drivers because the labor market is competitive.) This in turn makes the firm's marginal cost of such movements lower. Since the market for freight services is competitive, this lower marginal cost results in lower rates on average to those who pay freight bills (shippers or consignees). These lower rates in turn flow through to consumers to the extent that links in the supply chain leading to consumer goods, in which such trucking services are a cost item, themselves operate competitively. The net result of cutting irregularity or night driving would thus be an increase in supply chain costs that would cause a leftward shift (reduction) in the aggregate supply function for consumer products.

We can tell an analogous story about the role of the reduction in hours supplied by currently irregular drivers, in the event irregularity is prohibited, as a measure of the productive output that would be lost. We have less confidence in applicability of this story, as we are not completely confident the hours equation is correctly specified (see Section V below).

Estimating Total Social Costs. Unlike the case of a shift in a supply function due the imposition of a unit tax, the implied leftward shift (reduction) in supply is caused by a real increase in the utilization of social resources. So the resulting loss of consumer surplus, most of which is transferred to producers, represents, in equilibrium, a real social opportunity cost to consumers. Hence the correct measure of the social cost in this case is not a deadweight loss (the difference between the consumer surplus lost and the producer surplus gained), but the total reduction in consumer surplus. For the present, we treat the loss in consumer surplus as equal to the gain in producer surplus, as this is in turn estimated by calculating the increased costs of production caused by regulatory changes (1) and (2). This amounts to assuming that the demand for trucking services is perfectly inelastic, and the supply is perfectly elastic, even after all adjustments involved in having the economy return to general equilibrium take place. Thus, for instance, we are ignoring any intermodal shifts in response to higher trucking costs (any such shifts would probably modestly decrease the present estimate). However, since the total loss in consumer surplus is the relevant measure, these simplifications will cause a much smaller proportional impact on the results of the calculation than similar ones would in a case in which only a deadweight loss is at issue.

Let's consider the total social cost of policy change (1) (requiring "regularity"), using the results from the wage equation. The coefficient on the proxy we constructed for irregularity (a binary variable) -.0196. It is statistically significant at the 14.5% level, which means it is estimated relatively imprecisely, limiting our confidence in the estimate's numerical value (see below, Section IV for a full discussion of this equation). Under the assumptions in Section II, in equilibrium we expect that the typical irregular driver gets on average more miles (or more paid hours, where applicable), and so makes about the same annual income as a regular driver, other things equal. If we prohibit irregularity, then these drivers will have to be paid slightly less than 2 cents per mile more on the smaller number of miles they will then run.

Using the average annual miles from the Driver Survey of 112,000 as an estimate of the total annual miles run (hence not trying to explicitly capture any implied change in miles), this increase amounts to $2,195 per year in higher per mile wages over fewer miles under a no irregularity policy for the average irregular driver, in order to restore his or her wages to their approximate pre-regulatory change level. Hence society will pay that much more in higher freight rates for the freight each irregular driver now hauls, under our simplifying assumptions, if irregularity were prohibited, and all drivers perfectly complied with the prohibition.

If we treat all drivers (including owner-operators) like the average driver in our mileage-paid subset, and using figure (estimated elsewhere in this study) of 955,500 road drivers operating commercial vehicles, and we assume that 23.4% of this entire population was "irregular" (the same percentage as was irregular in our subset), this means that 223,500 drivers in the whole population would have to be paid about $2,200 in higher per-mile rates, while making fewer miles. So, this method of summing up the marginal costs over drivers produces an estimated total social cost to end consumers of $492,000,000 (a bit under $500 million) per year.

Let's consider the total social cost of policy change (2), limiting night driving to eighteen hours per week, using the results from the wage equation. First we need to translate this limit into a number that is meaningful in terms of our variable measuring night driving as a percentage of all driving on the last trip. We utilize the mileage-paid regression sub-sample, since we will use a regression coefficient estimate in the calculation. The hours reported for the last full week are 66.3 at the mean of the sub-sample, and at the mean of percent driving in the sub-sample, 75.3% of these were driving hours. So we estimate the weekly driving hours as 75% x 66.3 = 49.9 hours. A limit of 18 hours per week would thus represent 18/49.9 = 36% of weekly driving time. Next we need to adjust for the fact that the variable we have to measure the percent of night driving is the percent of driving time on the last completed trip that took place between the hours of 11:00 p.m. and 7:00 am., and the hours relevant to the potential policy change are 12:00 midnight and 6:00 a.m. If we assume a uniform distribution of this driving over the eight hour interval in question, the percentage of driving time our respondents have that occurs between 12:00 midnight and 6:00 a.m. should be 75% of the value we record for the longer period. Hence, the percentage of night driving measure by our variable that represents the limit proposed is 1/.75 = 1.333 times 36%, or about 48%. This is approximately equal to the percentage of night driving we record at the seventy fifth percentile of our distribution of the percent of night driving variable. So, this suggests that about one quarter of our sample will be affected by an eighteen hour limitation.

To calculate the marginal effect of this limitation, we will compute the increase in wages estimated to be required to shift someone at the ninetieth percentile of the percent night driving distribution down to the seventy fifth percentile. Then to estimate the total social cost we will scale this up for the whole over-the-road driver population by applying this change to one quarter of that population. The ninetieth percentile night driver has 66.7% of his or her driving at night, and to cut this level to the 46.7% of the seventy fifth percentile night driver is a drop of 30%. The point estimate of the effect of the percent of night driving on the wage is -.0415. This estimate is statistically significant at the 6.25% level, and so is a bit more precise than that associated with irregularity. This estimated value has the consequence that the elasticity of the wage with respect to the percent of night driving at the mean of the wage, but the ninetieth percentile of the night driving distribution, is -.0415 x

(.667/.303) = .091%. Hence, a 30% drop in the percent night driving should be associated with approximately a 30 x .091% = 2.74% increase in the wage, or .027 x \$.303 = \$.0083 per mile. On an average annual mileage of 112,000, this is about \$930 per year. Applied to one quarter of the estimated 955,500 regional and long haul road drivers, this gives a total social cost estimate of \$222,150,000.

Last, for comparison, let's consider the total social cost of policy change (1), using the results of the hours equation. The estimated coefficient on the proxy variable for irregularity is approximately twelve hours. Although this estimate is statistically significant by standard conventions, for theoretical reasons we are much less confident that this is a correct estimate (see below, Section V, for a complete discussion of the hours equation). Assuming that subtracting 12 hours per week (or 624 hours per 52 week year) from the approximately 223,500 irregular drivers in the population captures the number of productive hours that would need to be replaced due to a prohibition of irregularity, the industry would need to purchase 139,500,000 more hours of work than before. If we assume that all these hours can be supplied at the margin by incumbent drivers, at the marginal rate of \$7.01 per hour calculated elsewhere in this report from a regression on CPS driver data, the total annual social cost would be about \$978,000,000, or around twice as high as the estimate arrived at from the wage equation. (It would be possible to calculate this estimate using other assumptions, such as assuming that some new drivers have to be attracted and that this would require higher wages, but we neglect this until such time as this second equation is placed on a more sound theoretical footing.)

The Wage Equation in Detail. The wage equation is based on the idea that firms pay approximately their marginal revenue product to drivers. The left hand side variable is the nominal wage rate; the model is restricted to a sub-sample consisting of those employee drivers who reported a mileage rate of within a reasonable range, which excludes owner-operators (who get high mileage rates that include truck payments or who get percentage of revenue) and local drivers (who generally get hourly pay, or in rare cases, percentage of revenue). The N is approximately 170, and all regressions are weighted to reflect the different sampling rates at high traffic and low traffic interview sites. The weights ensure that the results reflect the population sampled, which is intended to be drivers passing through truck stops in the upper Midwest during the summer and fall of 1997, and hence, an approximation to the population of drivers passing through the upper Midwest during that time. We are thus implicitly assuming that this slice of the driver population is representative of all the truck drivers who will be significantly affected by the proposed changes to the Hours of Service for regional and long haul drivers.

The right hand side variables are (1) human capital variables that affect the revenue productivity of the driver's work input, (2) operational features that reflect the level of revenue likely to be generated by that work, and (3) operational or institutional factors that may affect reported mileage pay directly. After some experimentation as to which proxies work appropriately and which don't, in the first group are: occupational experience and its square (occexp and occexp2, in years; the squared term to permit an expected non-linearity--that the marginal effect should decrease), firm tenure (tenure--in months), education level (hsplus--binary for high school or higher versus less than high school), minority status (minority--binary), and whether the driver has a clean driving record (unclean--binary, with value one if reported an accident or moving violation in a commercial vehicle in the preceding 12 months). In the second group are type of equipment (dry box--binary for standard dry van—thought to be a more competitive segment--versus other), a length of haul proxy (regional--binary for regional or not, broken at 500 miles of reported typical run length), and the size of the firm (fsize--measured as number of total drivers). In the third category go union status (union-binary), whether the driver is paid for any non-driving time (paid--binary; to permit either a trade-off between mileage pay rate and receiving pay for other duties, or a "good jobs-bad jobs" effect which would cause them to march together), an interaction between union and pay for non-driving time (unionpd--to pull out from "paid" the effect of union drivers who normally get paid for nearly all non-driving time), and the two policy relevant variables based on the information on the last full trip cycle--irregularity (irreg1-binary) and percent of night driving (nightper--continuous).

In the currently standard version of this model we have the results shown in the table below. The adjusted R^2 (a measure of the proportion of variance in the dependent variable predicted by the independent variables) is slightly more than .298, which is quite decent for a cross section model. To interpret this table, note that "actmrate" is the left hand, or dependent variable, and the variables below it in a column are the right hand side, or independent variables.

actmrate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
union	-.0366932	.0170644	-2.150	0.033	-.0703718	-.0030146
paid	.0157242	.0124254	1.265	0.207	-.0087987	.0402471
unionpd	.1643136	.0527365	3.116	0.002	.0602321	.268395
hsplus	.0169313	.0145652	1.162	0.247	-.0118148	.0456774
occexp	.0055928	.0023794	2.351	0.020	.0008968	.0102888
occexp2	-.0001591	.0000777	-2.046	0.042	-.0003125	-5.66e-06
tenure	.000287	.0002486	1.154	0.250	-.0002036	.0007776
minority	.0101269	.0193478	0.523	0.601	-.0280581	.0483118
irreg1	-.0195682	.0181354	-1.079	0.282	-.0553605	.0162241
nightper	-.0415537	.0269278	-1.543	0.125	-.0946988	.0115913
drybox	-.02911	.0164022	-1.775	0.078	-.0614814	.0032615
regional	.0060165	.0194155	0.310	0.757	-.0323021	.0443352
fsize	2.21e-06	1.26e-06	1.760	0.080	-2.69e-07	4.70e-06
unclean	.0050014	.0136551	0.366	0.715	-.0219484	.0319512
_cons	.2396454	.0210524	11.383	0.000	.1980961	.2811948

Let's interpret the coefficients on our two policy variables.

1) Since irregularity (irreg1) is a binary variable, we can read the results from the point estimate: being irregular lowers the reported nominal mileage rate by approximately two cents per mile. Since for theoretical reasons we expect a negative sign on this coefficient, the significance level is determined by a one-tailed test, and so is half the level reported above for the standard two-tailed test, or .141. Thus, our confidence in this estimate is relatively low.

2) For the percentage of night driving (nightper), we need a little more interpretation. The coefficient is approximately negative .041. At the mean values of both variables,

this gives an elasticity of the predicted wage with respect to the percentage of night driving of .041 x (.278/.303) = .038. This implies that at the means, a 1% increase in the percentage of night hours will be associated with a .038% drop in the mileage rate. Thus, a 10% increase in night driving percentage (from 27.8% to 30.6%) would be associated with a .38% cut in the mileage rate (or about $.001). To give an example different from the one used in the calculation of marginal social cost in Section III, this suggests that cutting out all night driving (i.e. cutting it by 100%) for those at the mean levels of pay and night driving would raise their mileage rates by about 3.8%, or around $.0115 per mile (slightly more than a penny per mile). Since for theoretical reasons we also expect a negative sign on this coefficient, the significance level is also determined by a one-tailed test, and so is half the level reported above for the standard two-tailed test, or .0625. Therefore we are reasonably confident of this estimate.

The other coefficients in the equation tell a reasonable story. I briefly discuss their interpretations to fill in the context for the policy results.

3) The coefficient on the union indicator variable added to that on the union-paid interaction tell us that union drivers (all of whom receive some kind of pay for non-driving work) have a mileage rate that is approximately 13 cents per mile higher than nonunion drivers; this is consistent with our background understanding of the large union premium observed (especially in LTL and specialized TL union operation, which we find describes all or nearly all of the union drivers in our sample).

4) We expect schooling at the level that is useful in alternative jobs to improve the reservation wage of drivers, and the coefficient on the indicator hsplus estimates the value of this at about 1.6 cents per mile. Even applying a one-tailed test (which cuts the significance level from .247 to .124) this estimate is imprecise.

5) Occupational experience and its square are both estimated precisely; at the mean of experience (15 years) and of the predicted wage ($.303) the point estimates imply that a 1% change in occupational experience is associated with a .27% increase in mileage rate. This says that at the means, 15 months of experience is worth a little less (.8) than a penny a mile in pay rate.

6) The coefficient on firm tenure is imprecisely estimated (applying a one-tailed test puts the level at .125), but has the expected sign. The point estimate says that at the means (4.5 years and $.303 per mile wage) 12 months of firm tenure is worth about a third of a cent per mile, so three years would be worth about a penny per mile.

7) The coefficient on minority is opposite to that which other empirical work would suggest, but it is also so imprecisely estimated that it could have the expected sign. We interpret this to be due to the small number of minorities in the sample, combined with the fact that blacks, the largest minority group in the sample, are more often union members (with high pay) than is true on average, while Hispanics, the next largest group, are less often union members.

8) We expect the coefficient on the indicator for equipment type to be negative, since drybox captures whether the trailer hauled is of general purpose or specialized purpose, and competition and potential competition are both expected to be higher with general purpose equipment. The point estimate is relatively precise, and says that general purpose equipment is associated with about 3 cents per mile less pay.

9) The coefficient on indicator for regional work is of the expected sign. Rates to shippers are slightly lower on a per mile basis on longer runs (due to spreading fixed costs), and this is reflected an estimate of slightly higher mileage pay for runs under 500 miles. However this estimate is so imprecise that it doesn't tell us much.

10) The coefficient on firm size (measured as the total number of drivers) is small, but precisely estimated. It implies that at the mean predicted wage ($.303) and firm size (1,130 drivers), an increase to the size of the largest TL firm (about 12,000, or a 1,000% increase) would be associated with a 2 cents per mile increase in the wage rate.

11) Last, the coefficient on the bad driving record measure (unclean) is opposite the expected negative sign, but it is so imprecisely estimated that it could be zero or have the right sign. We interpret this imprecision to be due to either errors in self reporting, or possibly due to mismeasurement for present purposes because the only drivers whose job prospects are determined by their recent driving record are the subset who have recently changed jobs. Another alternative is that given turnover levels in some parts of the industry, firms are not trying to filter out drivers with bad records.

All in all, when interpreted these coefficients tell a reasonable story, and one that is generally consistent with our background understanding of industry practices and institutions. We are therefore reasonably confident that this specification gives a theoretically acceptable first cut at capturing the relationship it is designed to measure, and therefore also gives an theoretically acceptable, albeit empirically somewhat imprecise, first cut at providing the basis for measuring social cost.

The Hours Equation. The labor supply equation is based on the idea that given the decision to work as a truck driver at a given a wage rate, plus the level of need the driver has for income and various operational constraints that limit or enable the completion of runs (such as the policy-relevant variables of the level of irregularity or night driving), the driver will choose the optimal number of hours to work. We assume a recursive two-stage structure to this estimation problem: the driver's wage is first predicted from the wage equation, and then this predicted wage is inserted in the labor supply equation as an independent variable (instead of using the reported wage). We are assuming thus that we can capture the effect in each equation separately of variables which we think affect both (including our policy variables), without simultaneity or identification issues. In a more extensive project we would construct a formal utility maximization model to make explicit the structure of the assumptions implicit in this equation, and identify whether there are any cross-equation restrictions needed between the wage equation and the hours supply equation, and whether more sophisticated estimation techniques might be required. In the absence of this step we are less confident of the results from this equation than we are of those from the wage equation. However, we have produced a reasonable ad hoc specification, which we think provides a rough first cut at the estimation of labor supply decisions for incumbent drivers, although it is potentially subject to revision.

Our left hand side variable is the total work hours reported by the respondent for the preceding seven days. This is undoubtedly measured with some error, and although the survey asks for the hours actually worked, as opposed to the hours logged, we expect the main error to be an under reporting of total hours. We believe this would either be because the driver might be unwilling to report hours which actually exceeded the regulatory limits, even anonymously to an interviewer, or because the driver's recall over a seven day period might be influenced by what he actually logged during that period, which is likely to especially involve the under reporting of non-driving work time. We attempt to control for this to the extent possible.

On the right hand side we have four groups of variables. The first measure direct incentives to provide hours: the predicted wage from the wage equation, and its square (wage and pwage2—the latter to permit backward bending labor supply at high wages), whether the driver receives any pay for non-driving work, (paid--binary), and an interaction between this and the driver's union status (unionpd), to separate out the effect of union drivers who get paid for most non-driving time. In the second group are variables that are proxies for other motivational or control factors that affect labor supply choices. These include the number of economically dependent children who reside with the driver (numchild), how much other income the household has (othinc), and a measure of the last time the driver had 24 hours off duty at home (lasthome, in days), and the driver's union status (union--with the expectation that this directly gives the driver somewhat more control over hours worked, along with the higher wage it brings). In the third group are operational factors that limit or enable miles to be made and/or runs to be completed. In this group are the percent of non-driving work hours (pernodrv), whether the driver has short runs or not (regional--which here means 500 miles or less as an average reported run), and the two policy relevant variables: whether the driver has an irregular schedule (irreg1), and percent of night driving (nightper). The last group is a single measure of the likelihood of under reporting weekly hours. It is an interaction between the percent of non-driving time reported (recall this is from the last trip), and a measure of the number of hours less than sixty which the driver reported for the last week's total (devper). This is to capture that portion of under reporting that is due to the practice of saving log time for driving hours by reporting non-driving work time as off duty, thus causing weekly hours to be less than 60 when market conditions (e.g. delays at shippers or consignees) prevent the full exhaustion of driving hours.

In the current version of the labor supply equation, we have coefficient estimates presented in the table below. The adjusted R^2 (a measure of the proportion of the variation in the dependent variable which is predicted by the independent variables) is .354, which is very decent for a cross section estimation. To interpret this table, note that "hrsweek" is the left hand side, or dependent variable, and the variables below it in a column are the right hand side, or independent variables.

hrsweek	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
pwage	248.4684	229.9141	1.081	0.281	-205.4052	702.3419
pwage2	-234.8226	258.4523	-0.909	0.365	-745.0334	275.3882
irreg1	11.98129	5.257417	2.279	0.024	1.602616	22.35995
nightper	-.4083473	7.311694	-0.056	0.956	-14.84237	14.02567
pernodrv	26.86129	9.704851	2.768	0.006	7.702945	46.01964
union	61.72147	16.37457	3.769	0.000	29.39643	94.04651
regional	-7.902634	3.009758	-2.626	0.009	-13.8442	-1.96107
paid	1.111417	4.9635	0.224	0.823	-8.68703	10.90986
unionpd	-81.2913	23.102	-3.519	0.001	-126.897	-35.68562
devper	4.65155	.6484444	7.173	0.000	3.371455	5.931644
age	1.519493	1.369906	1.109	0.269	-1.18484	4.223826
age2	-.0161974	.0158648	-1.021	0.309	-.0475161	.0151213
numchild	-.4580857	1.002579	-0.457	0.648	-2.437278	1.521106
othinc	-.000048	.0001116	-0.430	0.668	-.0002683	.0001724
lasthome	.1558112	.1238967	1.258	0.210	-.0887734	.4003957
_cons	-18.89825	42.25458	-0.447	0.655	-102.313	64.51654

Let's interpret the coefficients on our two policy variables.

1) The coefficient of regularity (irreg1) is precisely measured, and says that an irregular schedule is associated with almost 12 hours additional hours reported per week. Under our maintained assumptions that irregularity primarily reflects the demands of the flow of freight, this would suggest that cutting out all irregularity (permitting only one tour of duty per 24 hour period) would be associated with a drop in 12 hours worked for the typical driver. Note that our measure is based on total hours reported to us, not the (possibly smaller) number of hours logged under the current regulations.

2) The coefficient on percentage of night driving is measured so imprecisely as to be meaningless, so this specification does not tell us much about this question.

The rest of the coefficients on variables in the equation tell a reasonable story. We briefly discuss their interpretations to provide the context for understanding the equation as a whole.

3) The coefficients on the predicted wage and its square have the expected sign (positive for pwage, and negative for pwage2). At the means of the variables, together they imply that a 1% increase in the predicted wage would be associated with a .49% increase in hours supplied. To give an example, this would mean that a $.03 per mile increase in the wage (10%) would be associated with about 3.25 more hours per week (4.9%). However, even using one-tailed tests (since we have a definite expectation as to sign), these coefficients are imprecisely estimated (14% and 18% significance levels), so although the magnitude of these coefficients is reasonable, our confidence in these results is not very great.

4) The percent of non-driving work time enters in two ways. Its simple coefficient is estimated very precisely (1% significance level), and implies at the means of both variables that a 1% increase in percent non-driving work time is associated with a .1% increase in total hours worked in the last week, as reported by survey respondents to interviewers. At the means this translates into an increase from 24.7% non-driving work time to 27.2% (10%) being associated with .6 more hours of reported weekly work time (1%). In addition, the coefficient on the interaction of percent non-driving time with the number of hour less than 60 reported is very precisely estimated (significance level as high as can be measured). This coefficient has the interpretation that at the means of both variables, a 1% increase in this interaction term is associated with a 1.5% decrease in reported weekly hours. So, at the means, and starting from a mean reporting deviation of 5.2 hours, the same 10% increase in the percent non-driving work time that is associated with .6 morc hours of reported work time is also associated with an increased reporting deviation that drops reported weekly hours by approximately 1. Thus, the net effect of a 10% increase in the percent of non-driving work time is a .4 hour decrease in reported time, and the pattern of the coefficients is strongly consistent with the hypothesis that under reporting of non-driving time is reflected in the hours reported to the interviewer for the last week.

5) The coefficients on the union indicator and the interaction indicator of union with paid are both estimated very precisely (significance levels of less than 1%). Together they tell us that union drivers (all of whom are paid for some non-driving time) report approximately 20 hours less of work per week.

6) The coefficient on regional is very precisely estimated (significance level of better than 1%). It tells us that regional drivers (500 miles or shorter average reported run) report approximately 8 hours less per week than those with longer runs. From the descriptive statistics we expect that regional drivers work similar but slightly fewer hours than longer haul drivers, but that their non-driving time is likely to be a larger proportion of their total time (as we'd expect time spent at shippers and consignees to be a proportionally larger). Since we have controlled for this effect with the variable for percent non-driving time, this result is sensible.

7) The coefficients on age and its square are opposite in sign to our casual expectation (that older drivers tend to slow down a little, and not work as many hours, controlling for number of children and the like). The results are not precise enough to be very clear, however. And we note that in our sample age and its square are correlated quite highly with experience and its square (about +.55 in each case), so we may be unable to distinguish the effect of experience (which met expectations in the wage equation) from an age effect for this reason.

8) We have no particular expectation about the coefficient on the number of children, since children cause both an interest in working more hours to get more income, and also in getting home, and these may conflict. It is estimated too imprecisely to tell us much, although the current point estimate would imply at the means that having one more economically dependent child at home is associated with about .5 less reported hours per week.

9) Our expectation for other income is negative, but even with a one-tailed test it is estimated imprecisely (significance level of .33). The current point estimate implies that at the means, a doubling of other household income from $11,000 to $22,000 would be associated with about .6 fewer reported hours per week, but this doesn't tell us much, due to the lack of precision in the estimate.

10) Our expectation for the coefficient of days since last home for 24 hours is positive, on the assumption that getting home requires working more hours on average, rather than cutting a week short. On this assumption a one-tailed test makes this coefficient moderately precise (significance level of just over 10%). The point estimate implies that at the means (being gone 7.7 days and working 66 hours per week), in increase of an extra week since last at home is associated with reporting 1.25 more hours per week.

All in all, when interpreted these coefficients tell a reasonable story, and one that is generally consistent with our background understanding of industry practices and institutions. However, the results are not as clean as those in the wage equation, and for this reason as well as the theoretical questions about proper specification that are potentially relevant here, we are quite a bit less confident in these results.

Future Directions. In this first attack on the problem we have attempted to construct a prototype methodology for generating estimates of the marginal and total social costs involved in simplified versions of two of the policy changes being considered with respect to the Hours of Service of commercial motor vehicle operators. The actual numerical estimates are reported in Section III. The prototype we have developed makes use of the unique survey data on truck drivers collected by the University of Michigan Trucking Industry Program, and while it is relatively primitive and *ad hoc* in its present form, it is potentially capable of validation, extension, and refinement in several ways

If future work were to be undertaken on this topic, there are a number of ways we could proceed. The following list is not exhaustive. First, we would hope to make use of extensions to the UMTIP Driver Survey data set, if the results of the Wave 2 administration of this survey were to be available in time. This would potentially increase the precision of our estimates by increasing N. Second, we would attempt to put the entire enterprise on stronger theoretical foundations. We would construct a formal utility maximization model for the choice behavior of drivers on whom we have data, and we would use this model to provide a specific theoretical justification for the specification of one or more regression equation systems. Then we would attempt to devise more formal tests of key assumptions, to the extent permitted by the data, such as the assumption made in Section II about the labor-leisure tradeoff of road drivers. (It might also be possible to test this assumption empirically by properly specifying an annual and/or a weekly earnings equation, and testing for the effect of our policy variables in it--with the expectation that they should have small effects if we have properly accounted for other influences, if the assumptions in Section II are correct.) Third, we would attempt to more precisely model the particular changes being considered, by constructing proxy variables that more closely track the potential changes being considered, including the different options as to how many working and off-duty hours will be permitted. We could also potentially construct variations consequent upon assuming different levels of compliance. Fourth, we would explore several ways in which it might be possible to refine the estimates of total social cost, given the point estimates from the equation system. We could attempt to account for a demand function for trucking services that is not perfectly inelastic (e.g. by estimating intermodal shifts). We could use more sophisticated assumptions about the relationships between irregularity in the sub-sample and in the entire population, and utilize more information about relevant distributions than just the mean. Fifth, we could construct more formal confidence intervals for the total social cost estimates.

1.3.3: Industry Impact.

Hours of service changes will likely have a great impact on the economic conditions of the industry. The proposed regulations attempt to create a broadly customized set of rules designed to make trucking safer and healthier. These new rules will change the way the industry works, assuming the FHWA finds a way to obtain broad industry compliance. Some of the most current suggestions include limitations requiring carriers to schedule drivers for a regular period of rest each day, in effect limiting their flexibility in assigning driver duty time; creating a definite weekly off-duty period during which drivers could get two actual nights sleep; allowing some flexibility for long-haul drivers who could take a shorter break at the end of one week of work and a longer break at the end of two weeks of work; and limiting night time driving (12:00 AM to 6:00 PM) to 18 hours per week. Researchers will study these regulations and develop frameworks within which they can analyze the impact of the change. Using institutional and operational knowledge developed from previous research, experience, and UMTIP industry case studies, researchers will estimate the operational effect of changes on various industry segments and types of operations, quantifying these effects to a first approximation. In this task researchers will not try to estimate the impact of regulatory changes on intermodal shifts, nor will they attempt to estimate the impact on the economy as shippers and consignees adapt to the change.

In studying the proposed options we do not find any explicit restrictions requiring a significant amount of regularity. While we refer below to some regulatory impact on operations that might occur as the result of a regulatory change, we have avoided drawing conclusions or inferences based on imprecise definitions. For this reason we excerpt proposed changes in the analytic text. Note that we attempted to model the impact of irregularity on wages and hours of service above, as we originally understood that proposed regulations would require regularity, but have restricted analysis here to the proposed regulatory options forwarded to us by the Office of Motor Carriers.

We have found nothing in the proposed HOS regulations that would suggest drivers would behave in any different way than they do now without a dramatic change in enforcement strategy. Currently the average driver is not in compliance with the present HOS regulations and nothing in the proposed regulations suggests this will change. Although the proposed rules might encourage regularity (or at least discourage backwards rotation of schedule), we find nothing in these rules that requires regular schedules. We also find nothing to prevent extensive forward rotation that would shift the driver's daily cycle so extremely as to disrupt sleep patterns entirely. Finally, we find nothing in the proposed rules to govern the operation of sleeper teams, perhaps the fastest-growing operations in trucking.

Industry impact can be separated into three different components. We can expect different effects from different aspects of the proposed changes. We will evaluate each of the proposed changes for likely impact on the industry.

Option A: Status quo hours of service limitations.

Text:

Status quo. All definitions, requirements, exemptions, exceptions, and interpretations remain the same.

In the first section of this report we showed that a majority of intercity truck drivers do not adhere to the current HOS rules, even in the broadest sense of weekly hours of service limits. The lack of adherence is not a minor issue. To a significant extent, drivers are not merely adjusting their work time to fit their personal circadian schedules. On the contrary, they are using loopholes in the current regulations to extend their work hours and playing the odds that they will not be caught. Indeed, with more than 400,000 motor carriers registered in interstate commerce — most of them quite small — government enforcement agencies require far more resources to enforce the law than they have available. Compliance must be voluntary or self-enforcing.

It appears, from the analysis presented in this report, that under the current legal regime (current FLSA, current limitations on union organizing, etc.) the cost of compliance would primarily be borne by the current violators. Without addressing how compliance can be secured, it appears that the unionized sector, including LTL and package carriers, comes relatively close to compliance. It also appears that owner operators (for whatever reasons) also come close to compliance. The number of new drivers needed in those sectors therefore would be minimal. Most new drivers would be needed by the TL industry, which has the greatest unfulfilled demand for drivers.

Weekly maximum hours. The most extensive violators appear to be in the non-union truckload sector, with somewhat more violations among those pulling dry boxes, suggesting the TL general freight sector may be most out of compliance. We have not had time to analyze the data for firm size effects, but we suspect the biggest violators are relatively small TL general freight carriers; these carriers tend to be extremely competitive. We expect therefore that the greatest proportion of the cost associated with returning to compliance would be borne by this segment of the trucking industry.

In the analysis we presented above, the cost of this compliance primarily comes from the demand for more drivers. According to the calculations above, the trucking industry would need to hire between 56,330 and 130,443 new drivers, depending on the extent to which drivers currently working less than 60 hours can work more hours. In our estimation, it would be unrealistically optimistic to expect to hire the minimum drivers as estimated above because their particular work schedules are defined by their operations; most likely the industry would need to hire closer to 130,000 drivers than the converse. Most of these additional drivers would work for lower-paid TL carriers facing a typical turnover rate of 100% today, suggesting the burden of the estimated driver wage increase mostly will fall on the TL carriers, since their wages are markedly lower than the wages in LTL and wages will have to rise to attract enough labor to satisfy the demand.

Finally, although we have not had the time to analyze differential effects by industry sub-sector, from the Form M (filed with the BTS) we find that the average carrier employs approximately 1.1 drivers per power unit. Assuming this average usage fits the TL industry (and particularly thinking about smaller carriers, the assumption makes sense), the industry will need between 51,209 and 118,585 additional power units {(56,330 ÷ 1.1) and (130,443 ÷ 1.1)}. While reduced usage by individual drivers (due to compliance with the 60 hour limit) might allow additional slip-seating of units (multiple drivers assigned to a single truck) it is impossible to estimate the impact without analyzing use patters very closely. Since the truck manufacturing industry built and sold 209,483 Class 8 tractors to set a new record in 1998, we can expect the price of trucks also to rise as the demand increases. With new truck prices running approximately $100,000, the cost of increasing the truck fleet could range between $5.121 billion and $11.859 billion, though much of the demand for additional trucks initially would be absorbed by used truck purchases that would reduce the cost. We have not calculated these economic effects beyond the trucking industry's need for drivers due to the lack of time, but it appears that the needed supply of trucks will produce a boom in the truck manufacturing industry, offsetting some of the negative economic effects. Additional human resource needs would include additional mechanics and other service personnel, and additional support personnel to administer the industry growth. Potential offsetting reductions might include modest disintermediation from truck to intermodal or rail, but continuing intense service demands for trucking service will limit that shift.

All of these costs might be minimized or eliminated were drivers' time to be used efficiently. Recall from earlier analysis that if we saved 25 percent of drivers' wasted, unpaid time we would eliminate the need for additional drivers. The same efficiency gain would be realized from the cost of equipment discussed in the previous paragraph. This suggests the current system wastes billions of dollars of driver time, reflecting the opportunity cost of drivers' labor time (unpaid labor time offset by excessive weekly hours) as well as billions of dollars in wasted opportunity cost of equipment, as a $100,000 truck spends about 25% of its time collecting dust. Again, time and resource constraints make it impossible for us to evaluate this complex ripple effect at this time.

Daily maximum hours. The driver survey suggests the current daily maximum hours limits are violated relatively frequently. The data collected in our survey may not exactly show what drivers are doing (though with more time and funding for analysis we may be able to learn more from the data) but it does suggest a pattern worth noting. Reflecting back on the data in Table 43 we can see that at the 75th percentile, drivers worked 14 hours — nearly the absolute maximum for a single shift and two hours less than the absolute theoretical legal maximum for a 24 hour period. At the 90th percentile for the full sample drivers work 18 hours, clearly beyond the legal limit. The total for local and regional drivers is 16 hours at the 90th percentile and 19 hours for long-haul drivers. Without looking very closely at the pattern of hours reported we cannot tell exactly what drivers may be doing but we can infer that at least a significant number of them are working more hours than they are supposed to work. Figuring that the typical driver takes a couple of hours off during a day to eat and take care of personal sanitation we can infer that at the 75th percentile drivers probably are not getting an eight hour break; certainly this must be true for long-haul drivers at the same percentile. The distribution of this variable may be affected by the location at which the surveys were administered, as it may not be close to the average long-haul driver's pick up or delivery point (where we would find most wasted hours).

The cost of compliance with current daily maximum hours limits is less clear. To the extent that drivers are exceeding their daily limits, work time would have to be reduced to reach compliance. This might cause some portion of the freight to arrive or be picked up later than promised or currently experienced, at some undetermined cost to truckers, shippers, and receivers. Clearly, however, as with weekly hours, wasted driver time accounts for enough of the difference to suggest that efficient use of drivers' time might save enough time to bring them into compliance.

The data suggest here also that the long-haul TL industry would absorb most of the cost of compliance. The TL industry has the biggest problem currently and would have the biggest adjustment coping with current weekly maximum hours rules. The chronic driver shortage reported by carriers induces them to get the absolute maximum out of each driver, and maximum effort by each driver is consistent with the continuous use of capital. The TL industry would find it most difficult to comply with daily limits because of demands shippers put on the carriers in a competitive environment.

The LTL industry, both regionally and nationally, tends to operate in a rhythm, that adequately protects most drivers from over work, and the high degree of unionization contributes to that outcome. From our research we think the regional LTL business is structured around pickups and deliveries that must be made in successive days, and hours of work beyond about 12 per day are not practical. There are only about 12 hours between the time the drivers bring the freight to outbound terminals and the time the freight must be delivered to inbound terminals in preparation for making the next day's deliveries. The long-haul LTL business might find it more difficult to comply except evidence suggests they already comply due to extensive conditioning and due to their concern with liability. While a TL company (particularly a small one) might close down and re-form under a new name after losing a lawsuit, an LTL company has too much capital investment, network investment, and marketing exposure to take such an action.

Option B: One-Size-Fits-All (12-12).

> Text:
>
> All drivers must have a minimum of 12 consecutive hours off duty, and may work up to 12 consecutive hours (with no distinction between driving and non-driving). The 12 consecutive hours for work will include all rest and meal breaks.
>
> All drivers must have at least a 58 hour weekly (7-consecutive day) off duty period of time. This would allow 60 hours of work in a 5 day period.

Daily scheduling. While neither this nor any other proposed reform institutionalizes consistency of schedule, this proposed reform at least infers consistent scheduling in an indirect way. As discussed above, the regional LTL industry would seem to have the least difficulty conforming with this schedule, as most freight follows the overnight rhythm. The ability to use the driver for 12 hours regardless of activity (driving or labor) would give the carriers more flexibility. We are not sure how much of this additional capability the carriers might use but it allows them to adjust according to the demands on their business. The national LTL industry might also seem to be able to live with this as they now use their drivers for less than 10 hours of driving at a time (and at least the union carriers do not require drivers to do other work) and would have the additional flexibility to use drivers beyond 10 hours if necessary. Both industry segments probably would have difficulty with this rule because it would reduce overall labor time somewhat; the rule specifies that the 12 hours includes all breaks, so the net effect might be to reduce total daily labor by as much as 10 percent or as little as zero. Assuming drivers work 11 hours per day for five days per week, that gives them a 55 hour work week, which is about what we would expect in the industry.

The long-haul TL industry, at the other extreme, would have to make major changes to adjust to this schedule. Our information suggests that drivers currently work far more hours than this rule would allow. In fact, data in Table 43 show half of the drivers in the TL industry would have to reduce their hours of work to achieve compliance. If other reforms caused the reduction in driver wasted time, as discussed above, the effect might be minimized. That is, since the median long-haul driver drives only 9 hours daily, this might not affect the driving labor experience of drivers at the median. However, note that at the 75th percentile long-haul drivers drive 12 hours, suggesting that the only way they could comply would be by eliminating non-driving hours entirely. This may be possible under the current compliance procedure (drivers log their non-driving labor time as off duty), this probably was not what the regulators would have expected. In sum, the long-haul TL industry probably would have to hire about 50 percent more drivers than they currently have, assuming they actually complied with the regulation and assuming no change in the current framework that does not discourage shippers and consignees (and even carriers) from wasting drivers' time.

Regional trucking generally looks closer to LTL than to the long haul trucking industry. While data are sketchy, the tables in this report suggest they fall approximately in the middle between local and long haul, depending on the measure. They are more likely on average to perform labor other than driving than the long-haul TL people, though the latter waste their time in larger blocks. It is difficult to generalize among such a wide set of possibilities, in terms of industry segments and markets, so conclusions are difficult to make based on the proposed regulation and the current work schedule. Work schedules vary quite widely due to industry segment.

Weekly scheduling. Proposed regulations would allow two days of rest, or at least two nights of sleep, at the end of a work week. The regional LTL industry already is structured in this way, or at least as closely as any other group. The typical regional LTL driver begins his work week Monday evening or night and works 5 "shifts" of driving and labor and ends up back at his home domicile by Saturday morning (some might add an additional shift to reach maximum hours and earnings or make service requirements for the carrier). While the new regulations would further limit flexibility of these firms with respect to extra driving (because of the requirement of 58 consecutive hours off once per week) they would have the least effect on these drivers.

The long-haul LTL industry is not scheduled in this way. While we believe they could adapt to this schedule they would have to do so with some effort and dislocation. Their operations currently depend on a mix of regular bid runs, on-call drivers, and casual drivers. City drivers (pickup and delivery) have reasonably regular shifts, ordinarily are paid by the hour, and probably stick pretty closely to the recommended HOS limits and schedule. Regular bid road drivers run steady operations between cities and haul the most predictable freight. As a result, their schedules are predictable and can most likely conform to the daily and weekly HOS rules. Lower-seniority irregular road drivers who maintain a position on a seniority list ("road board") are called in to work as the carrier is able to "close out" a trailer and send it to another destination. Such destinations vary, but sharp cutoff times needed for regional LTL aren't needed in national LTL and hence the daily discipline is not as critical. Bigger terminals have a higher number of bid drivers, normally, and may be able to create relatively restricted time windows during which daily dispatch can occur (though this does not seem to be an issue according to proposed HOS rules we have received from FMCSAHS). Weekly regularity is a bigger problem, since that is not a current requirement. We have no way to estimate the cost of compliance for this industry, though it probably is something they could do with some loss of efficiency.

Both the regional and national LTL industry may find it difficult to adapt structurally to different options regarding hours of service. Currently these carriers take both business and regulatory constraints into consideration when planning terminal networks. That is, they consider the metropolitan area in which they may pick up and deliver freight (or where they have appropriate freight density) along with the distances between terminals between which they transfer freight throughout their network. Any changes in daily hours of service regulations could cause them to move terminals closer together or farther apart. We cannot readily estimate the cost of such readjustment but we thought it important to mention that some readjustment undoubtedly will take place.

The regional trucking industry (particularly TL and other-than-general-freight) probably could adapt to this change relatively easily also, since they are better able to get drivers home on weekends or on a weekly basis. Currently these carriers advertise "home weekends" as a recruiting tool, so undoubtedly their workers and potential workers view this as a benefit. While they scarcely comply with the current 60 hour weekly limit (Table 39 shows them working 60 hours per week at the median), their biggest problem probably will come more in adapting to the 60 hour limit than in adapting to the schedule providing for 58 hours of continuous off duty time weekly.

The long-haul TL industry would find it the most difficult to adapt. Currently drivers are working through this period and view lengthy delays on the road as tiring time wasters. Since these drivers typically sleep in their trucks and would have to spend this time in truck stops when their weekly break occurs on the road, they may not achieve the level of rest anticipated by the rule even if they obey the regulation. For analytic purposes, however, it might make sense to divide the long-haul TL industry into two broad conceptual segments.

Smaller TL carriers run their drivers long distances and likely will have their drivers spending weeks on the road. While we have not analyzed this phenomenon in detail, research suggests the smaller carriers have fewer alternatives to this form of operation. That is, if they dispatch a driver on a long cross-country run they alone are responsible for locating freight for the return trip. We suspect their inability to locate freight on a timely basis contributes to the "wasted time" phenomenon observed from the survey. Larger carriers may be more likely to locate freight for the return at this distance, though every carrier has some trouble maintaining freight balance over long routes and between far-flung city pairs.

Perhaps the biggest advantage larger carriers (or perhaps more precisely, carriers with denser regional concentrations and freight lanes) have over smaller carriers is some ability to relay freight from one region to another. The ability to relay freight from one driver to another would allow the carrier to keep drivers within a reasonable proximity of home and allow them greater opportunities to return them home for the 58 hour breaks. Without this option, long-haul carriers and their drivers would find it rather difficult to adapt to this regulation. We suspect that the unintended consequences might include a continuation of the current situation: drivers extend their overall hours of service by logging wasted time off duty, and will continue to maximize paid time on the road at all hazards.

Option C: General Rule (12-12)

Text:

1. All drivers must have a minimum of 12 consecutive hours off duty, and may work up to 12 consecutive hours (with no distinction between driving and non-driving). The 12 consecutive hours for work will include all rest and meal breaks.

2. Weekly. Drivers must have at least a 58 hour weekly (7-consecutive day) off duty period of time. This would allow 60 hours of work in a 5 day period.

Long-haul, Motorcoach Tour, Regional Less-than-Truckload, Scheduled Route Bus (10-2-12)

Long-haul, regional less-than-truckload, scheduled route bus, and motorcoach tour have the common meanings known in the motor carrier industry.

3. Daily. The regulations would require long-haul (e.g., truckload), regional less-than-truckload, scheduled route bus, and motorcoach tour drivers to have a minimum of 10 consecutive hours off-duty, and drive up to 12 hours. The regulation would allow these drivers to break the 12

hour work period with off-duty periods totaling at least two additional hours.

4. Weekly. The regulations would allow a two-week option for truckload, regional less-than-truckload, scheduled route bus, and motorcoach tour drivers. These drivers must have at least a 36 hour end-of-workweek off-duty period, including 2 consecutive midnight to 6 AM periods. This would allow up to 72 hours of work in the first 6 days of the 14 day period of time. After the 36-hour off-duty period, the driver may work up to 48 hours over workdays 8, 9, 10, and 11 of the 14-day work period, and then the driver must be off duty for at least 82 hours prior to returning to work.

Option C appears to be almost the same as Option B except that long haul drivers may have the ability to concentrate their work during the first week of work, allowing them the ability to minimize the cost inherent in the 58 hour extended rest period specified in Option B. The specifications are ambiguous in that they include only truckload or regional LTL (in this paper we do not analyze motorcoach drivers). The analysis that follows generally describes potential impact on any sector that could take advantage of this option.

This option might make it easier for TL carriers to comply with the regulations, but we are not certain how much impact the difference represents. The 36 hour break after the first 72 hours of work, since it includes two night-time sleep periods, may well encourage safer operations. Drivers probably could squeeze this period (essentially two nights and a day) into one weekend day without seriously affecting their ability to make long runs. It is not clear, however, how far a long-haul driver could go before running out of hours on the return trip. The consequences of running out of hours before returning home on the return trip are severe, as the driver must take 82 hours off (3.4 days); such an extended enforced break might induce extremely dangerous practices on the part of the drivers to avoid such a penalty. The alternative might be to encourage appropriate practices by ensuring that drivers' time is not wasted; that is the most powerful predictor in our analysis above.

According to our research, approximately 25% of a long-haul driver's time is wasted loading, unloading, and waiting around. If this remains the case, it is not at all clear that a driver can cross the country, deliver a load, and pick up a load within the required time frame for two-week operations. Indeed, we know that the average driver can get in only 45 hours of driving per week in a two-week period according to this rule, forcing him to continue to log wasted time off duty in order to make his pickups and deliveries (he can make the long-distance run within the allowed time if he logs labor time as off duty, as he does now). For this reason it is quite unclear whether the rule will be effective or enforceable. On the other hand, if shippers and consignees were forced to pay for drivers' time on either end of a load (thereby enabling the carrier to pay for the driver's time), we probably would see less wasted time and less incentive for overwork. This phenomenon, called "moral hazard" (in this case on the part of shippers, consignees, and carriers) may be responsible for most of the abuses we see on a regular basis. If so, the proposed change in regulatory structure will be doomed at the outset.

The impact on regional LTL is unclear. We do not quite see how this might affect regional LTL one way or the other. This business sector is the most consistent and most likely to be able to stay with prescribed limits as suggested in Option B. The same is true for national LTL, though in either case this option might allow for uneven work scheduling and greater flexibility. On the other hand, carriers that take advantage of it one week would need to find replacement workers to complete the week's schedule during a second week. While this is possible (individual schedules can be set up on a two-week basis so that replacement workers can substitute for one regular employee for two days, another regular employee for the next two days, and so on), the advantages of such an operation (over Option B) are entirely unclear.

Option D: Night-time Differential (All Drivers, No Exemptions or Exceptions)

Text:

This option would limit driving between the hours of Midnight and 6:00 A.M. for all drivers to a maximum of 18 hours in a workweek.

General Rule (12-12)

1. Daily. All drivers must have a minimum of 12 consecutive hours off duty, and may work up to 12 consecutive hours (with no distinction between driving and non-driving). The 12 consecutive hours for work will include all rest and meal breaks.

2. Weekly. Drivers must have at least a 58 hour weekly (7-consecutive day) off duty period of time. This would allow 60 hours of work in a 5 day period.

Long-haul, Motorcoach Tour, Regional Less-than-Truckload, Scheduled Route Bus (10-2-12)

3. Daily. The regulations would require long-haul (e.g., truckload), regional less-than-truckload, scheduled route bus, and motorcoach tour drivers to have a minimum of 10 consecutive hour off-duty, and drive up to 12 hours. The regulation would allow these drivers to break the 12 hour work period with off-duty periods totaling at least two additional hours.

4. Weekly. The regulations would allow a two-week option for truckload, regional less-than-truckload, scheduled route bus, and motorcoach tour drivers. These drivers must have at least a 36 hour end-of-workweek off-duty period,

including 2 consecutive midnight to 6 AM periods. This would allow up to 72 hours of work in the first 6 days of the 14 day period of time. After the 34-hour off-duty period, the driver may work up to 48 hours over workdays 8, 9, 10, and 11 of the 14-day work period, and then the driver must be off duty for at least 82 hours prior to returning to work

This option has two primary dimensions. The hours-of-service dimension seems consistent with Options B and C. The impact of these aspects of the regulation on the industry has been analyzed above and will not be repeated here. The second dimension is the limitation on night-time driving. The following analysis assesses this impact.

The limitation on night-time driving would cause major restructuring in the LTL industry. Our research shows that most LTL carriers, especially in the regional industry, run throughout the night. The regional LTL industry, in particular, relies on night-time driving. Its primary niche is the overnight service lane, and the structure of operations requires night time driving. To summarize and simplify their operations, they pick up freight during the afternoon and bring it to a terminal where it is stripped off local trailers and reloaded on road trailers for delivery. The dock operation may take anywhere from 3 to 5 hours, after which the loaded trailers are dispatched over-the-road to a terminal or terminals in another city. The freight may be handled once or twice enroute during the night. In any case, the freight arrives at its destination terminal the following morning, is stripped off the road trailer and loaded onto a city trailer. A city driver ("pickup and delivery driver") takes the freight to the customer, and repeats the pickup process. This pattern ordinarily continues Monday through Friday, with most freight picked up and delivered on those days.

Variations on this theme apply to the inter-regional LTL carriers as well as to national package delivery carriers, much of whose revenue actually consists of regional and local freight. This description applies to package delivery operations, such as United Parcel Service and Federal Express, for example. National LTL carriers (along with inter-regional LTL carriers and package carriers) have wider variation in operation. The pickup and delivery processes are the same, but longer lanes mean that the intermediate dispatch can take place around the clock. Some carriers are structured such that inter-regional movement of freight will tend to happen on the same night-time lanes on which their over-night shipments travel, and some carriers are structured so that second- and third-day freight will travel during the day for at least some of its intermediate movement. In any case, the entire industry depends on night-time freight movement and any attempt to restrict it to 18 hours per week per driver would cause major restructuring. Indeed, since this restriction likely would restrict drivers to three days of work per week (less than full time), we suggest carriers might adapt by switching their drivers between night-time and day-time shifts throughout the week. While this would comply with the regulations, it would cause major damage to their biological cycles and making operations extremely dangerous. Alternatively, regulators could ban all night time driving, but resulting congestion and risk exposure probably would overwhelm the positive safety effects.

Our driver survey evidence suggests the problem of night-time driving is somewhat less severe than previously thought. The above section on night driving, including Table 64 through

Table 71, suggest that on average drivers already are well in compliance with such a proposed rule. The discrepancy comes at the extremes. People who are on the night shift perform all of their work during these hours, so as individuals they are far from compliance with a proposed 18 hour limit. This group includes those who drive for most regional LTL carriers, for package carriers, and probably for much of the inter-regional and national LTL industry. Those who drive for TL firms (particularly long-haul) may well drive a small enough percentage of their hours during this period that they would be in compliance. The problem is that these drivers work 80 hours at the 75th percentile and 96 hours at the 90th percentile, making the 18 hour limitation a minor issue in their work schedule but one that likely makes a minor contribution to their safety risk. Ironically, the drivers most likely to be compliant with the 60 hour limit probably are the very drivers whose industry would be altered dramatically or shut down as a result of such a regulation. Finally, while data are sketchy we think the LTL and package industry has a much lower than average accident rate, so we would be interfering with the operations of those carriers that contribute least to the nation's highway safety problem.

With greater funding and more time a more definitive analysis can be made. At this point, however, it seems to us this regulation would not achieve anywhere near enough benefit to justify the cost. We have not performed an economic analysis of this effect, but we could do so given more time for analysis.