ANALYSES OF FATIGUE-RELATED LARGE TRUCK CRASHES, THE ASSIGNMENT OF CRITICAL REASON, AND OTHER VARIABLES USING THE LARGE TRUCK CRASH CAUSATION STUDY

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The Large Truck Crash Causation Study (LTCCS) collected data on a random sample of approximately 1,000 crashes involving at least one large truck (gross vehicle weight rating of at least 10,000 pounds) during 2001-2003 where there was a fatality, an incapacitating injury, or a non-incapacitating, but evident injury. The study was a nationwide survey with 24 data collection sites in 17 states and the results were weighted to represent all nationwide crashes. For each crash, investigators collected data on all vehicles involved, including information from driver, witness, and police interviews and from driver logbooks. Investigators determined for each driver involved in the crash, whether there was driver fatigue based on the driver interview and other information such as log-books. Investigators also determined the critical reason for the critical event, from which an indicator of driver critical responsibility can be derived. In this analysis we focus on the drivers of large trucks involved in these large truck crashes. We used logistic regression to investigate the relationship between driver fatigue and driver critical responsibility and several explanatory variables: hours of driving, hours worked on day of crash, hours awake, hours of last sleep, hours worked last week, time of day, number of vehicles involved, day of week, and truck type. We found that the most important variables associated with driver fatigue were: hours awake, hours of last sleep, hours worked last week, and the number of vehicles involved. We found that the most important variables associated with driver critical responsibility were: hours of last sleep, hours worked last week, number of vehicles involved, and truck type.

DATA

The Large Truck Crash Causation Study (LTCCS) collected data on a nationally representative random sample of approximately 1,000 crashes involving at least one large truck (gross vehicle weight rating of at least 10,000 pounds) during 2001-2003 where there was a fatality, an incapacitating injury, or a non-incapacitating, but evident injury. The study was a nationwide survey with 24 data collection sites in 17 states. The survey was a stratified, clustered random sample. The nation was divided into 1,195 primary sampling units (clusters) which were grouped into 12 strata, defined by geographical region and degree of population. Two clusters were randomly selected from each stratum and all, or most, qualifying crashes in the selected clusters were investigated. Sampling weights are provided for each crash so that the weighted data represent all qualifying nationwide crashes.

For these analyses we excluded data where one or more of the crucial fatigue-related variables was missing. We only included the data from drivers of large trucks (defined as vehicle body type--GVEBODYTYPE--codes 60-64 or 66 to 78), since we wanted the analyses to focus on truck driver fatigue and responsibility. The resulting database had 706 observations (truck drivers) from 642 crashes with data from 23 of the 24 clusters. Our analyses used the SAS SURVEYLOGISTIC procedure to take into account the survey design and sampling weights. For these analyses we treated the missing data as if they were randomly missing and did not make any adjustments for the missing responses. For simplicity we also did not adjust our analyses to account for the one missing cluster; this means that our variance and statistical significance level estimates are slightly inaccurate.

Table 1 lists the variables used in our analyses. The dependent variables of interest are the indicators of driver fatigue and driver critical responsibility. Driver fatigue was determined by the investigators based on the driver interview, log-books, and other information[1]:

> **Source:** Determined by the Case Reviewer using all available information inputs. The primary data source here is the driver interview, however, due to the inaccuracies inherent in these data, the Case Reviewer should compare driver responses with other data sources including log book entries, time stamped fuel and toll receipts, carrier records, and other interview sources to determine the veracity of the driver responses. The final assessment of fatigue involvement is made from all of these sources and may include the on-site assessments of the NASS Researcher.

Since fatigue was not directly measured physiologically, but instead was determined indirectly from the driver interviews, log-books, etc., it is likely that the driver fatigue variable is strongly related to the driver's work schedule. Thus a strong relationship should be expected between the driver fatigue variables and hours of sleep and work variables, even if there was no physiological fatigue.

Driver critical responsibility is based on the Critical Reason for the Critical Event, OVEREASON or ACRREASON, determined by the investigators[2]:

> **Source:** Determined by Case Reviewer using all available information inputs. Primary sources include the scaled schematic, police report, driver interviews, witness interviews, and vehicle inspection results. It should be noted, however, that this may be a subjective decision based on the preponderance of available evidence.

We used this variable to define Driver Critical Responsibility = 1 as codes 100-199. Driver Critical Responsibility = 0 if OVEREASON is coded as 0 ("critical event not coded to this vehicle"), 200-299 (vehicle condition issues), 500-518 (highway condition issues), 521-528 (weather condition issues), or 530-999 (other issues).

[1] Description from LTCCS Analytical Users Manual.
[2] Description from LTCCS Analytical Users Manual.

Table 1. Variables used in the analyses.

Variable Name	Abbreviation	LTCCS Variable Name	Definition
Driver Fatigue	fatiguec	DriverFatigue	Indicates whether or not the driver in this vehicle was coded as being fatigued at the time of the crash. 1= Yes, 0 = No.
Critical Reason		ACRREASON, OVEREASON	Establishes the critical reason for the occurrence of the critical event. The critical reason is the immediate reason for this event and is often the last failure in the causal chain (i.e., closest in time to the critical precrash event). Although the critical reason is an important part of the description of crash events, it is not the cause of the crash nor does it imply the assignment of fault.
Driver Critical Responsibility	critresp2		1 if Critical Reason in 100-199, 0 otherwise.
Hours of Driving	drive	HoursDriving	Represents the number of hours the driver has been driving since he/she last had a break of at least 8 hours.
Hours Worked on Day	work	HoursWorked	Represents the number of hours the driver worked on the day of the crash.
Hours Awake	awake	HoursSinceSleep	Represents the number of hours that have passed since the driver has awoken from his/her last sleep interval.
Hours of Last Sleep	sleep	LastSleepHours	Represents the number of hours the driver slept (most recent sleep interval).
		LastWeekHours	Represents the total number of hours that the driver worked on his primary job during the 7-day interval preceding the crash.
		LastWeekMoonlight	Represents the number of hours the driver worked on his/her second job during the 7-day interval preceding the crash.

Variable Name	Abbreviation	LTCCS Variable Name	Definition
Hours Worked Last Week	last		Sum of LastWeekHours and LastWeekMoonlight
Time of Day	timeofday	CrashTime	Identifies the time of day of the crash.
Vehicle Count		VehicleCount	Documents the total number of vehicles that were involved in the crash. This includes all CDS, non-CDS, in-transport, and not in-transport vehicles.
Single Vehicle	singlev		1 if VehicleCount =1, 2 if VehicleCount > 1
Day of Week	dayofweek	Day	Identifies the day of the week that the crash occurred. 1 = Sunday, 2 = Monday, … 7 = Saturday.
		GVEBodyType	Identifies the body type for this vehicle. Large trucks are defined by codes 60-64 and 66 to 78.
Vehicle Type	typenum		1 or Single Unit Truck (SUT) if GVEBodyType is 60-64 or 78. 2 or Combination Unit Truck (CUT) if GVEBodyType is 66-77.

For each variable analyzed we present some summary statistics of their distribution. Table 2 gives the summary statistics for the numerical variables and Table 3 gives the frequency distributions for the categorical variables. These analyses are weighted by the sampling weights.

Table 2. Means and percentiles of LTCCS analysis variables.

Variable	**Mean**	**P0**	**p5**	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**	**p100**
Hours Slept	7.94	0.3	4.5	5.7	7.0	8.0	9.0	10.0	11.5	16.0
Hours Awake	6.50	0.1	1.5	2.0	3.5	6.0	8.8	11.6	14.0	38.6
Hours of Driving	3.98	0.0	0.3	0.5	1.5	3.5	6.0	8.0	9.5	24.0
Hours Worked on Day	4.72	0.0	0.5	1.0	2.0	4.3	7.0	9.4	10.9	16.8
Hours Worked Last Week	43.14	0.0	16.0	25.0	36.5	43.5	51.8	60.0	66.0	111.5
Vehicle Count	2.23	1.0	1.0	1.0	1.0	2.0	3.0	4.0	5.0	8.0

Table 3. Frequency distributions of LTCCS variables.

Variable	Value	Percentage
Driver Fatigue	1	11.91
Driver Critical Responsibility	1	46.57
Single Vehicle	single	25.33
Single Vehicle	multiple	74.67
Time of day*	0	1.40
Time of day	1	1.71
Time of day	2	1.64
Time of day	3	2.59
Time of day	4	1.32
Time of day	5	4.98
Time of day	6	4.99
Time of day	7	4.33
Time of day	8	8.66
Time of day	9	10.88
Time of day	10	7.34
Time of day	11	6.44
Time of day	12	5.69
Time of day	13	6.04
Time of day	14	9.57
Time of day	15	5.08
Time of day	16	3.56
Time of day	17	4.26
Time of day	18	2.25
Time of day	19	2.11
Time of day	20	1.48
Time of day	21	0.90
Time of day	22	1.80
Time of day	23	0.98
Day of Week	Sun	1.68
Day of Week	Mon	18.28
Day of Week	Tue	18.57
Day of Week	Wed	20.76
Day of Week	Thu	19.72
Day of Week	Fri	17.33
Day of Week	Sat	3.66
Truck Type	CUT	78.46
Truck Type	SUT	21.54

* Crash time of day rounded down to nearest hour, e.g. 0 is for crashes between midnight and 1 am, 1 is for crashes between 1 am and 2 am, etc.

Table 2 shows that at the median levels, the “typical” crash occurs after 3.5 hours of driving, the driver had been awake for 6 hours after a sleep of 8 hours, and worked a total of 43.5 hours the previous week on regular and moonlight hours. Of course, the actual numbers for a given large truck driver can be much higher or much lower than these.

Table 3 shows that driver fatigue occurs for 12 % of drivers of large trucks involved in large truck crashes with injuries or death, and that driver critical responsibility is assigned for 47 % of drivers of large trucks involved in large truck crashes with injuries or death. Note that these numbers are estimates of the national proportions of drivers of large trucks involved in large truck crashes with injuries or death, rather than being proportions of large truck crashes. If a large truck crash involves only one vehicle, driver critical responsibility is assigned to the driver for 80 % of those crashes. If a large truck crash involves multiple vehicles, driver critical responsibility may not be assigned to any driver, may be assigned to one of the drivers of large trucks involved in the crash, or may be assigned to a non-large-truck driver.

LOGISTIC MODELS FOR DRIVER FATIGUE

To analyze the relationship between driver fatigue and the explanatory variables, we fitted logistic regression models, taking into account the survey design and sampling weights. The general formulation is given by;

$$\text{P(Driver Fatigue)} = 1/\{1 + \exp[-(a0 + a1 \times X1 + a2 \times X2 + a3 \times X3 \ldots)]\},$$

where X1, X2, … are the explanatory variables (numerical or categorical) and a0, a1, a2, … are the coefficients. Equivalently, we have

$$\text{logit}\{\text{P(Driver Fatigue)}\} = a0 + a1 \times X1 + a2 \times X2 + a3 \times X3 \ldots,$$

where logit(p) = log{p/(1-p)}. Thus the logarithm of the odds of driver fatigue is a linear function of the explanatory variables. In this notation, P(Driver Fatigue) denotes the probability of driver fatigue given that the driver of a large truck was involved in a large truck crash with explanatory variables X1, X2, …

To fit these models, the first task was to determine suitable functions to represent the effects of the explanatory variables. The numeric explanatory variables and their abbreviations were: Hours of Driving (drive), Hours Worked on Day (work), Hours Awake (awake), Hours Slept (sleep), and Hours Worked Last Week (last). We compared the fits of logistic regressions for each variable X using linear, quadratic, and cubic functions:

- Linear: $\text{logit}\{\text{P(Driver Fatigue)}\} = a0 + a1 \times X$
- Quadratic: $\text{logit}\{\text{P(Driver Fatigue)}\} = a0 + a1 \times X + a2 \times X^2$
- Cubic: $\text{logit}\{\text{P(Driver Fatigue)}\} = a0 + a1 \times X + a2 \times X^2 + a3 \times X^3$

We plotted the fitted probabilities against the observed (weighted) proportions and selected the simplest model that followed the observed pattern reasonably well.[3] The selected formulations were: Hours of Driving (linear), Hours Worked on Day

[3] Initially we tried a stepwise approach to select the polynomial model. However in several cases (e.g., for hours worked on day), the stepwise approach stopped at a linear model when the graphical approach clearly showed a quadratic or higher order relationship was more appropriate.

(quadratic), Hours Awake (quadratic), Hours Slept (cubic), and Hours Worked Last Week (linear). For example, for hours slept, the logistic model is of the form:

logit{P(Driver Fatigue)}= $a0 + a1\times sleep + a2\times sleep2 + a3\times sleep3$,

$sleep2 = (sleep)^2$
$sleep3 = (sleep)^3$

We used a similar graphical technique to select models for the categorical variables. For time of day, we used four 6-hour groups, midnight to 5:59 am, 6 am to 11:59 am, noon to 5:59 pm, and 6 pm to 11:59 pm. For vehicle count, we grouped the data by single vehicle or multiple vehicle. For day of week, we grouped the data into Sunday, Monday to Friday, and Saturday. For truck type we used the two groups: Single Unit Truck and Combination Unit Truck. An indicator variable is created for each group. For example, for time of day, the model is of the form:

logit{P(Driver Fatigue)}= $a0 + a1\times TOD1 + a2\times TOD2 + a3\times TOD3 + a4\times TOD4$,

TOD1 = 1 if time of day is from midnight to 5:59 am, 0 otherwise.
TOD2 = 1 if time of day is from 6 to 11:59 am, 0 otherwise.
TOD3 = 1 if time of day is from noon to 5:59 pm, 0 otherwise.
TOD4 = 1 if time of day is from 6 to 11:59 pm, 0 otherwise.

This formulation uses the SAS “GLM” parameterization. By definition, the fitted coefficient a4 for the last class value, TOD4, equals zero.

The fitted univariate logistic models for the probability of driver fatigue based on Hours of Driving, Hours Worked on Day, Hours Awake, Hours Slept, and Hours Worked Last Week are shown in Figures 1 to 5, respectively. The black dots (not joined) are the observed proportions, rounding the hours to the nearest hour (hours worked last week are rounded to the nearest 5 hours). The area of each black dot is proportional to the total survey weight, so that observed x values with low survey weights appear small and very faint. The joined red dots are the predicted probabilities from the logistic regression. The joined blue squares are a smoothed curve fitted to the observed proportions using a LOESS smoother.[4] The Wald chi-square p-values[5] are listed under the title. This p-value tests if the plotted variable is statistically significant, i.e., tests if all the coefficients other than the intercept are equal to zero.

The Hours of Driving variable is borderline significant (p-value 0.055). Although the fitted model suggests that the probability of driver fatigue increases with hours of driving, we note that there is very little data for 10 or more hours of driving. Hours Worked on Day, Hours Awake, Hours Slept, and Hours Worked Last Week are all extremely significant (p-values < 0.00001).

[4] The LOESS smoother fits a linear regression model to the points in a local neighborhood of each x value.
[5] These calculations used SAS software which computes p-values using the asymptotic chi-square distribution, taking into account the survey design but without adjustment for the degrees of freedom.

Figure 1. Probability of being fatigued given a crash as a function of Hours of Driving,
Model with terms: Hours of Driving (linear).
Wald p-value for Hours of Driving = 0.05497
Size of black dot is proportional to total survey weight for observed value.

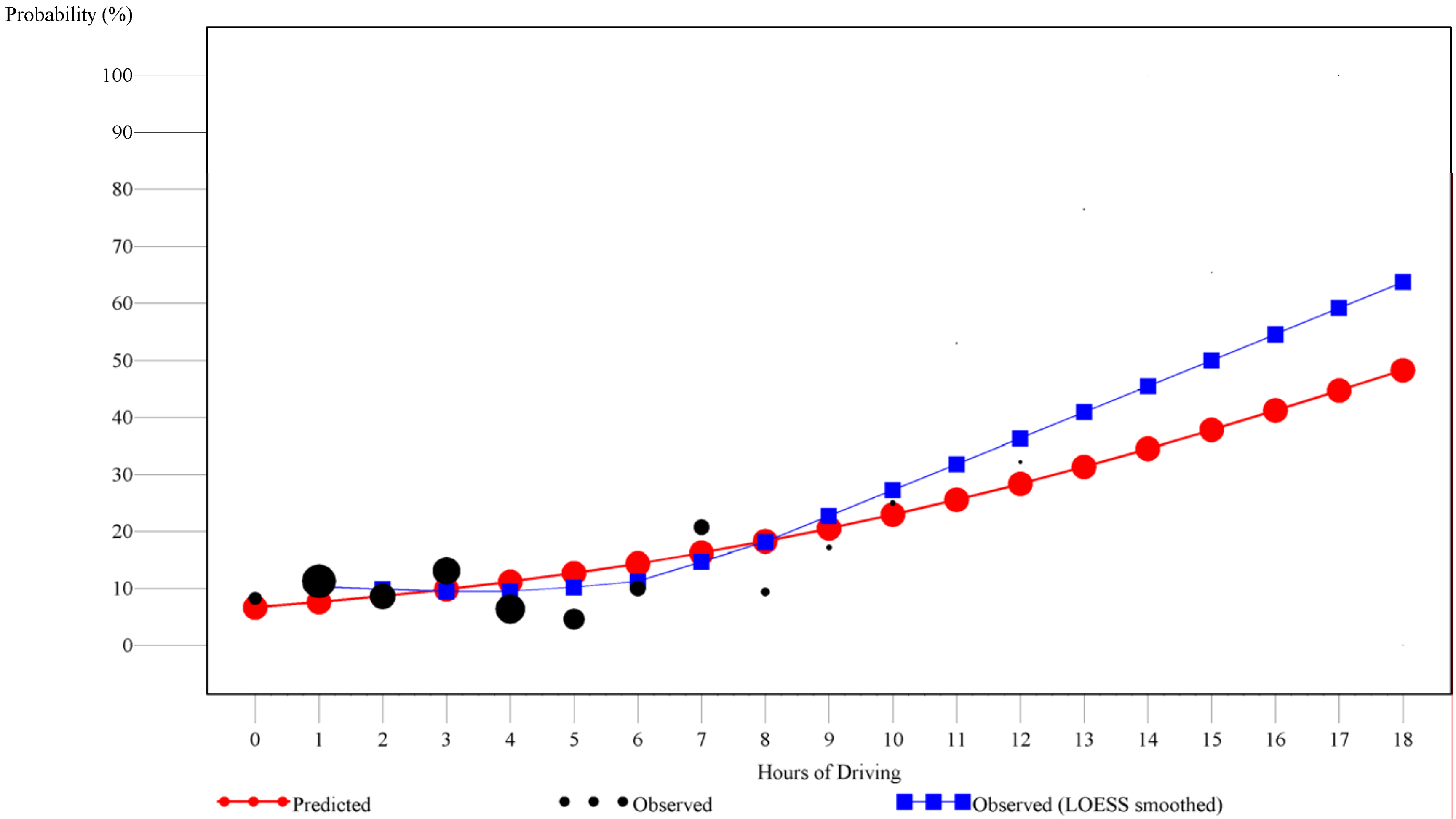


Figure 2. Probability of being fatigued given a crash as a function of Hours Worked On Day,
Model with terms: Hours Worked on Day (quadratic).
Wald p-value for Hours Worked On Day = 0.00000
Size of black dot is proportional to total survey weight for observed value.

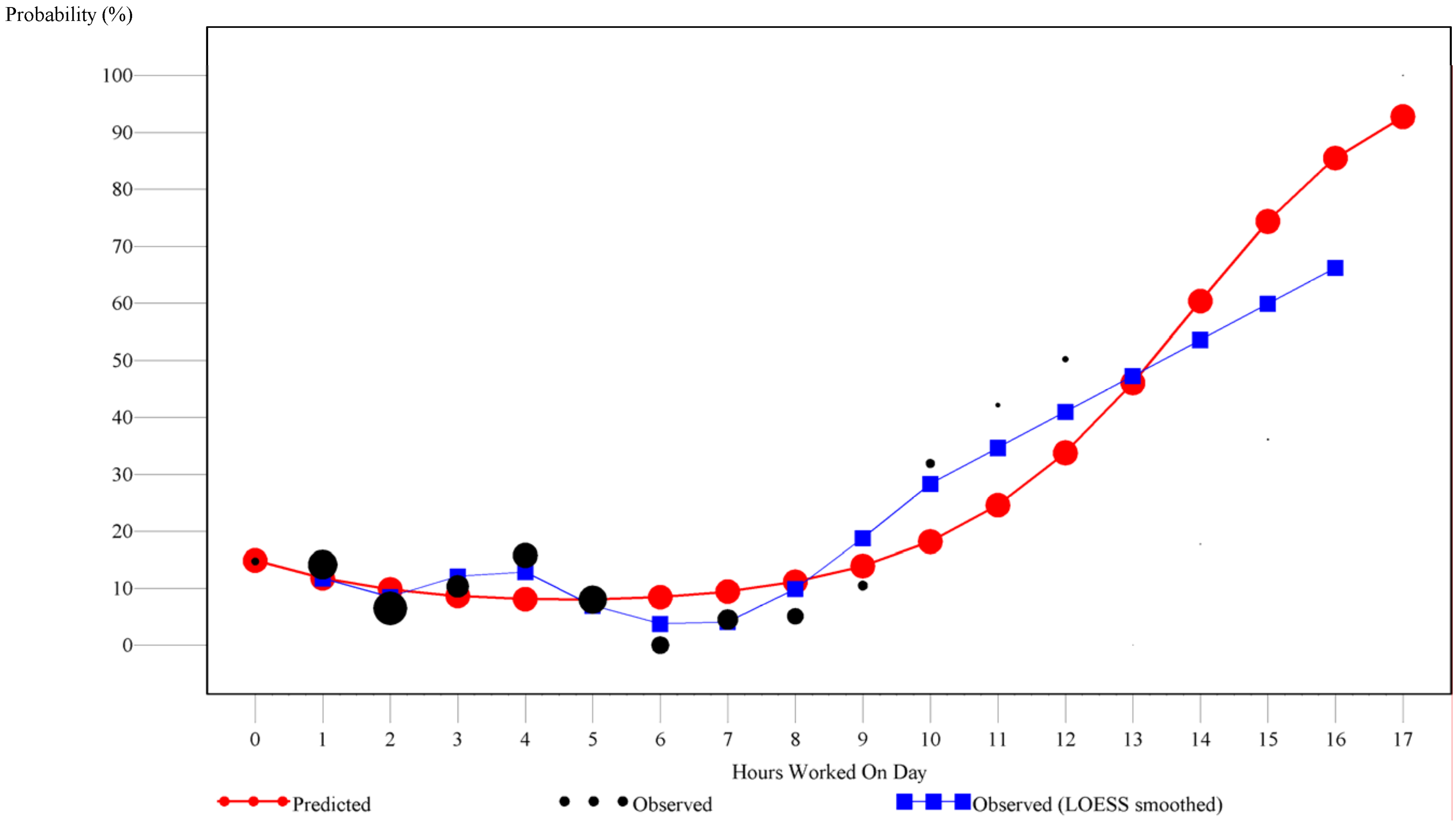


Figure 3. Probability of being fatigued given a crash as a function of Hours Awake,
Model with terms: Hours Awake (quadratic).
Wald p-value for Hours Awake = 0.00000
Size of black dot is proportional to total survey weight for observed value.

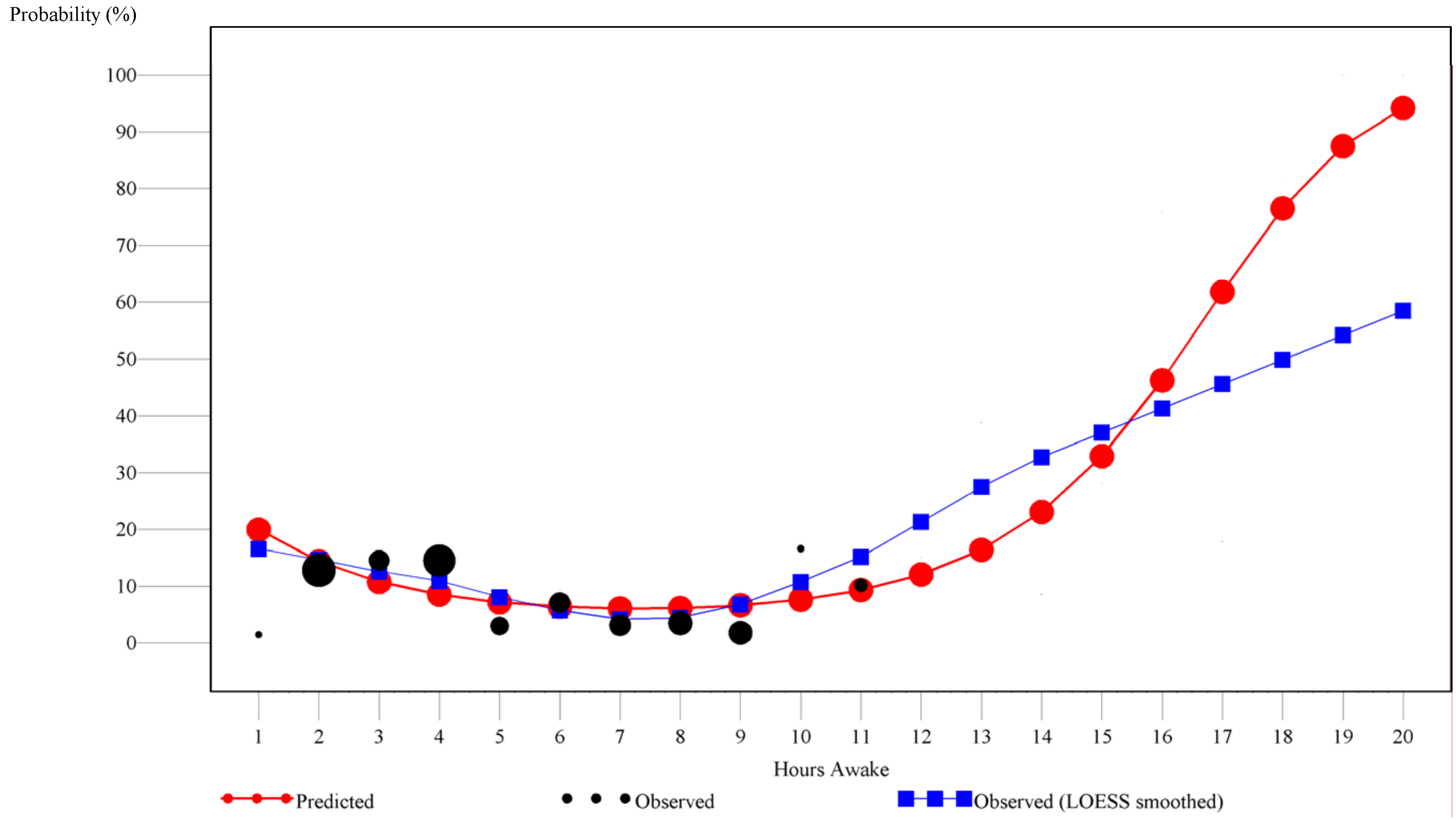


Figure 4. Probability of being fatigued given a crash as a function of Hours Slept,
Model with terms: Hours Slept (cubic).
Wald p-value for Hours Slept = 0.00000
Size of black dot is proportional to total survey weight for observed value.

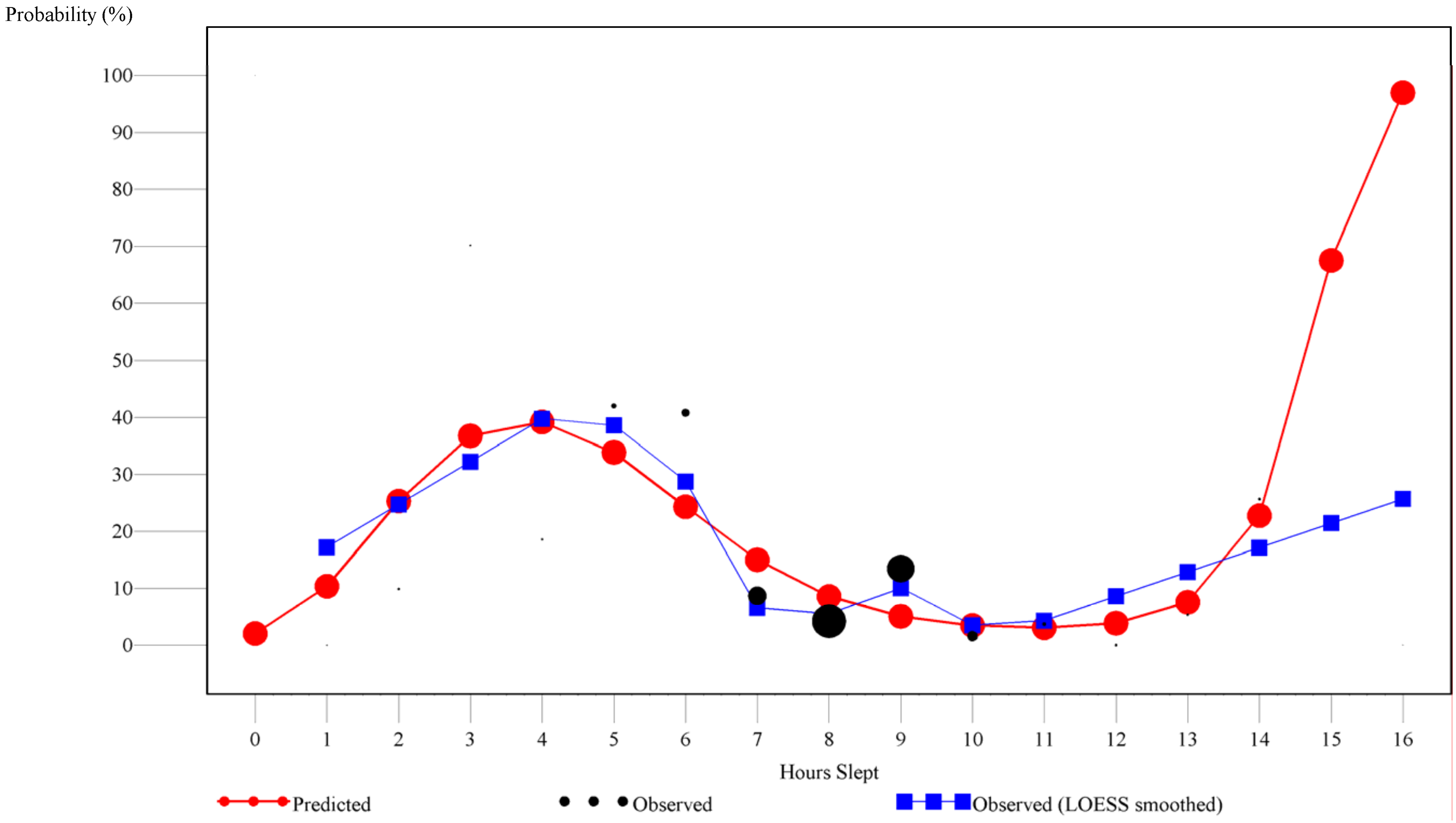
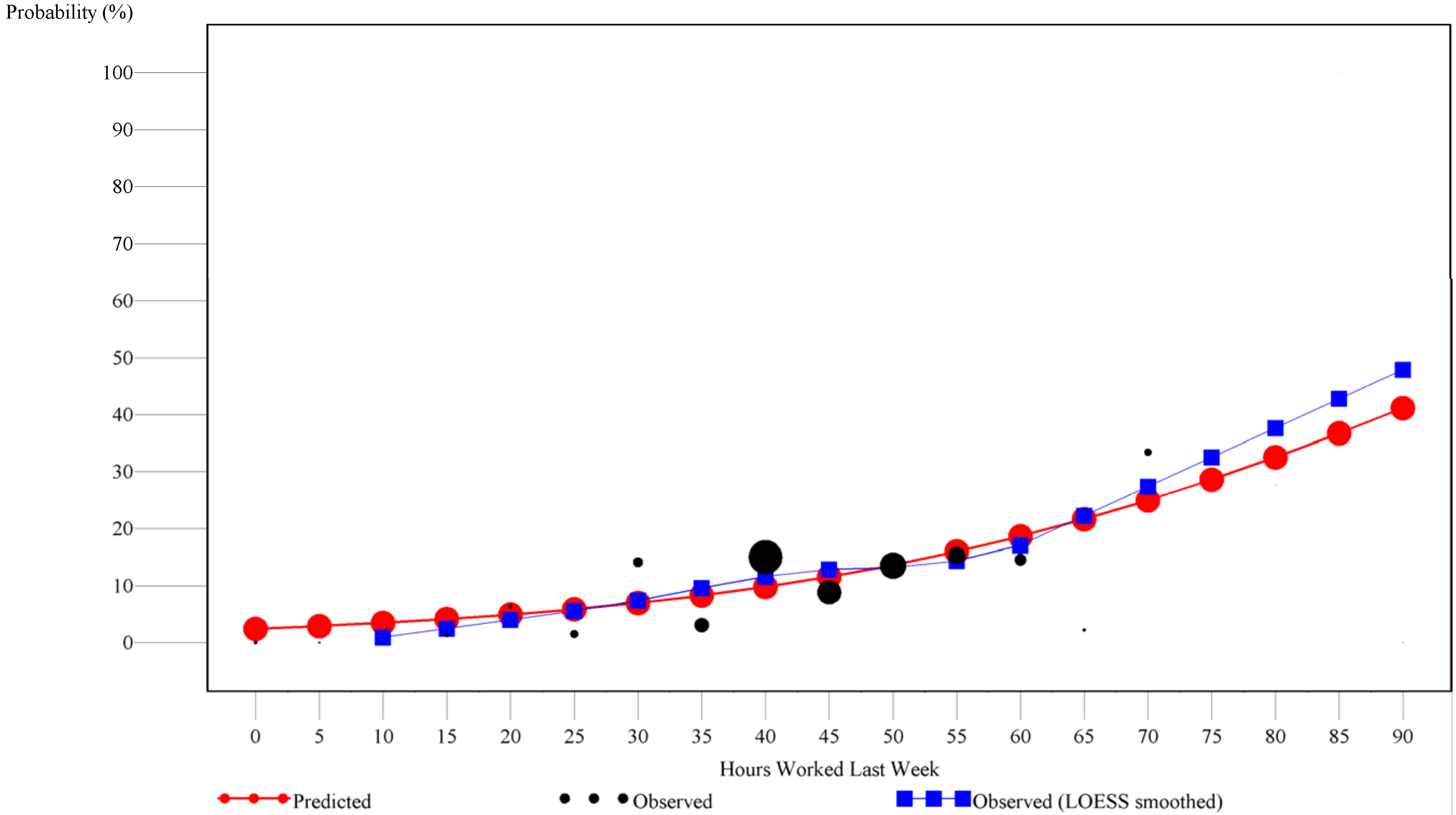


Figure 5. Probability of being fatigued given a crash as a function of Hours Worked Last Week, Model with terms: Hours Worked Last Week (linear). Wald p-value for Hours Worked Last Week = 0.00000

Size of black dot is proportional to total survey weight for observed value.



The logistic linear models for Hours of Driving and Hours Worked Last Week predict steady increases in the probability of fatigue with increases in hours. The model for Hours Worked on Day shows that the probability of fatigue begins to steepen after 9 hours. The model for Hours Awake shows that the probability of fatigue begins to steepen after 11 hours. The model for Hours Slept shows a much higher probability of fatigue after small amounts of sleep (2-6 hours) and after very large amounts of sleep (14+ hours). However the pattern after 14 hours of sleep is based on a small amount of data.

The Time of Day model (not shown) found a statistically significant association (p-value 0.004) and a higher probability of fatigue for the midnight to 6 am period. The Vehicle Count model (not shown) found a highly significant (p-value < 0.00001) association and gave a much higher probability of fatigue for single vehicle crashes (29 %) compared to multiple vehicle crashes (6 %). The models for Day of Week and Truck Type (not shown) were not statistically significant. Note that physiologically, we would not expect fatigue to be affected by the vehicle count, although it might well be affected by the other explanatory variables studied[6]. However, the statistical model using vehicle count shows that if a truck driver is involved in a crash, then the probability that the investigator determines driver fatigue is statistically significantly higher for single vehicle versus multiple vehicle crashes. In other words, after a crash has occurred, the fact that the crash involved a single vehicle would make it more likely that there was driver fatigue.

We next used a stepwise approach to build up a multi-variable logistic model for driver fatigue. Each candidate model is a combination of one or more of the selected univariate models, so that for example, the Hours of Driving is assumed to have a linear effect, Hours Worked on Day is assumed to have a quadratic effect, and Vehicle Count is modeled categorically as single or multiple vehicle. At each step, the most significant term was added to the model if its Wald chi-square p-value was less than 0.10. The least significant term was then subtracted from the model if its Wald chi-square p-value was 0.15 or greater. After building up the main effects model, we continued our process by adding and subtracting interaction terms in the same stepwise manner, where the candidate interaction terms are interactions between any of the selected univariate terms in the main model. (See the driver critical responsibility model, below, for an example).

We also required that the total degrees of freedom in the fitted model is at most 10 including the intercept, since the maximum available degrees of freedom equals the number of clusters with data (23) minus the number of strata (12), 23-12 = 11. Models with more than the maximum available degrees of freedom are unstable. An additional degree of freedom is needed so that the Hours of Driving term can later on be added to the final model.

[6] Plausibly, even the truck type could have a physiological affect on driver fatigue due to physical and psychological differences in driving different types of trucks.

The final model contained the following terms, in order of their selection: Hours Awake, Hours Sleep, Single Vehicle, Hours Worked Last Week, Hours Worked on Day. Since all 10 degrees of freedom were used in the main effects model, no interaction terms were included. Because the model has no interactions, the predicted change in the logit (i.e., the log odds of driver fatigue) when Hours Awake changes from a hours to b hours will always be the same, regardless of the values of the other explanatory variables. Similarly for the other main effects variables. However, the predicted driver fatigue probability and changes in that probability will depend upon all the explanatory variables. The coefficients of the model, standard errors, Wald chi-square statistics, and p-values are shown in Table 4.

Table 4. Final driver fatigue model coefficients.

Variable	Value	DF	Estimate	StdErr	WaldChiSq	ProbChiSq
Intercept		1	-4.38193	0.81	29.22	6.44E-08
sleep		1	1.69794	0.31	29.46	5.71E-08
sleep2		1	-0.30882	0.06	28.88	7.69E-08
sleep3		1	0.01379	0.00	24.65	6.88E-07
awake		1	-0.66924	0.26	6.88	8.69E-03
awake2		1	0.04080	0.01	13.64	2.22E-04
last		1	0.04027	0.01	11.75	6.07E-04
work		1	-0.09945	0.22	0.20	6.55E-01
work2		1	0.02032	0.01	2.87	9.01E-02
singlev	1	1	1.90409	0.38	25.26	5.00E-07
singlev	2	0	0.00000			

The p-values in Table 4 are for individual terms and estimate the statistical significance for testing that the individual coefficient is zero. For example, the p-value for the linear sleep term, keeping the quadratic and cubic terms in the model, is 5.7E-08. More useful is the p-value for each main effect as a whole, given in Table 5.

Table 5. P-values for main effects in final driver fatigue model.

Main Effect	P-Value
Hours Sleep	5.57E-10
Hours Awake	8.39E-06
Hours Worked Last Week	1.39E-02
Hours Worked on Day	6.07E-04
Single Vehicle	5.00E-07

Since the final model includes five main effects, the estimated driver fatigue probabilities depend upon the values of all those variables: Hours Awake, Hours Sleep, Single Vehicle, Hours Worked Last Week, and Hours Worked on Day. To compare the predictions of the final driver fatigue model with the predictions of the univariate models (e.g., Figures 1-5) , we computed predictive marginals. For example, to calculate the predicted marginal driver fatigue probability when Hours Awake = 4, we replaced all 706 values of Hours Awake by 4 and used the model to predict the probability of driver fatigue for each driver in the data set, assuming that their Hours Awake had been equal to 4 (instead of their actual values). We then averaged the predicted probabilities over all 706 truck drivers. The predicted marginals (not shown) for Hours Awake, Hours Sleep, Hours Worked Last Week, and Hours Worked on Day have very similar values to the univariate model predictions shown in Figures 3, 4, 5, and 2, respectively. The predicted marginals (not shown) for Single Vehicle also have very similar values to the univariate Single Vehicle model predictions (not shown).

In Figure 1, we found that if Hours of Driving was the only term in the driver fatigue model, then it was borderline statistically significant (p-value 0.055). The final driver fatigue model did not include Hours of Driving. To evaluate the effects of Hours of Driving in combination with other explanatory variables, we refitted the final driver fatigue model after adding in the linear Hours of Driving effect.

Figure 6 shows the predictive marginal driver fatigue probabilities for Hours of Driving for the final driver fatigue model with an extra Hours of Driving linear term. The Figure shows that Hours of Driving has almost no effect if the other terms are in the model. The p-value for Hours of Driving in this model equals 0.98, which tests whether the Hours of driving effect equals zero, if the other terms are in the model.

LOGISTIC MODELS FOR DRIVER CRITICAL RESPONSIBILITY

To analyze the relationship between driver critical responsibility and the explanatory variables, we fitted logistic regression models, taking into account the survey design and sampling weights. The general formulation is given by;

$$P(\text{Driver Critical Responsibility}) = 1/\{1 + \exp[-(a0 + a1\times X1 + a2\times X2 + a3\times X3 \ldots)]\},$$

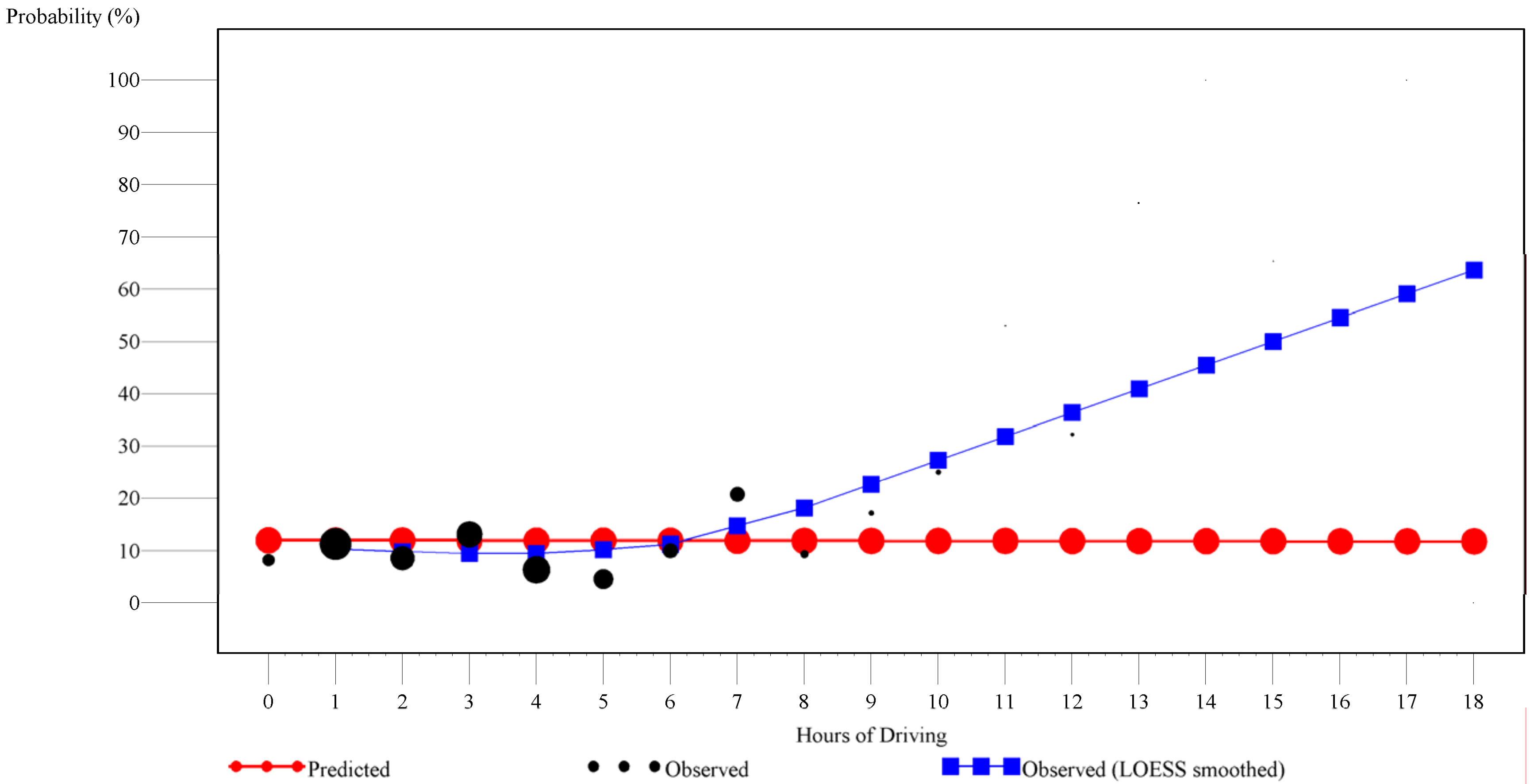
where X1, X2, … are the explanatory variables (numerical or categorical) and a0, a1, a2, … are the coefficients. Equivalently, we have

$$\text{logit}\{P(\text{Driver Critical Responsibility})\} = a0 + a1\times X1 + a2\times X2 + a3\times X3 \ldots,$$

where $\text{logit}(p) = \log\{p/(1-p)\}$. Thus the logarithm of the odds of driver critical responsibility is a linear function of the explanatory variables. In this notation, P(Driver Critical Responsibility) denotes the probability of driver critical responsibility given that the driver of a large truck was involved in a large truck crash with explanatory variables X1, X2, …

The model-fitting procedure was analogous to the driver fatigue models. The first task was to determine suitable functions to represent the effects of the explanatory variables. We plotted the fitted probabilities against the observed (weighted) proportions and selected the simplest model that followed the observed pattern reasonably well. The selected formulations were: Hours of Driving (linear), Hours Worked on Day (linear), Hours Awake (quadratic), Hours Slept (quadratic), and Hours Worked Last Week (cubic). For the categorical variables, we used the same formulations as for the driver fatigue models. For time of day, we used four 6-hour groups, midnight to 5:59 am, 6 am to 11:59 am, noon to 5:59 pm, and 6 pm to 11:59 pm. For vehicle count, we grouped the data by single vehicle or multiple vehicle. For day of week, we grouped the data into Sunday, Monday to Friday, and Saturday. For truck type we used the two groups: Single Unit Truck and Combination Unit Truck.

Figure 6. Probability of being fatigued given a crash as a function of Hours of Driving,
Final model with Hours of Driving added.
Wald p-value for overall model = 0.00000
Wald p-value for Hours of Driving = 0.97823
Size of black dot is proportional to total survey weight for observed value.



Model terms are: Hours of Driving (linear), Hours Slept (cubic), Hours Awake (quadratic), Hours Worked On Day (quadratic), Hours Worked Last Week (linear), Single Vehicle

The fitted univariate logistic models for the probability of driver critical responsibility based on Hours of Driving, Hours Worked on Day, Hours Awake, Hours Slept, and Hours Worked Last Week are shown in Figures 7 to 11, respectively. As for driver fatigue, the black dots (not joined) are the observed proportions, rounding the hours to the nearest hour (hours worked last week are rounded to the nearest 5 hours). The area of each black dot is proportional to the total survey weight, so that observed x values with low survey weights appear small and very faint. The joined red dots are the predicted probabilities from the logistic regression. The joined blue squares are a smoothed curve fitted to the observed proportions using a LOESS smoother. The Wald chi-square p-values are listed under the title. This p-value tests if the plotted variable is statistically significant, i.e., tests if all the coefficients other than the intercept are equal to zero.

Figure 7 is for Hours of Driving. The Hours of Driving term is not statistically significant (p-value 0.42). The fitted model shows a slight upward trend, possibly attributable to the unusually high observed probability of 70 % at 7 hours of driving. There are also predictions of 81 % at 11, and of 100 % at 13, 14, and 18 hours, but these have very low sampling weights and so appear very faint. Similarly, there are low predictions of 32 % at 12 and 0 % at 17 hours, again based on very low sampling weights.

Figure 8 is for Hours Worked on Day, which is even less statistically significant (p-value = 0.98) with no discernable trend.

Figure 9 is for Hours Awake. The p-value for this model is 0.087. The fitted quadratic model decreases slowly from 1 hour to 10 hours and then increases slowly from 10 hours to 20 hours. However the observed driver critical responsibility proportions show considerable scatter.

Figure 10 is for Hours Sleep. The p-value for this model is 0.075. The fitted quadratic model decreases rapidly from 90 % at 0 hours to 40 % at 8 hours and then increases rapidly up to 90% at 20 hours. However the bulk of the weighted data are from 6 to 10 hours of sleep. For four or more hours of sleep, the pattern is similar to the driver fatigue versus sleep model shown in Figure 4. The data for hours 0 to 3 are sparse and highly variable.

Figure 11 is for Hours Worked Last Week. The p-value for this model is 0.086. The fitted cubic model shows a sharp rise from 0 to 35 hours, after which the probability is almost constant. However, the available data are sparse and scattered at high numbers of hours.

Figure 7. Probability of Driver Critical Responsibility given a crash as a function of Hours of Driving,
Model with terms: Hours of Driving (linear).
Wald p-value for Hours of Driving = 0.42252
Size of black dot is proportional to total survey weight for observed value.

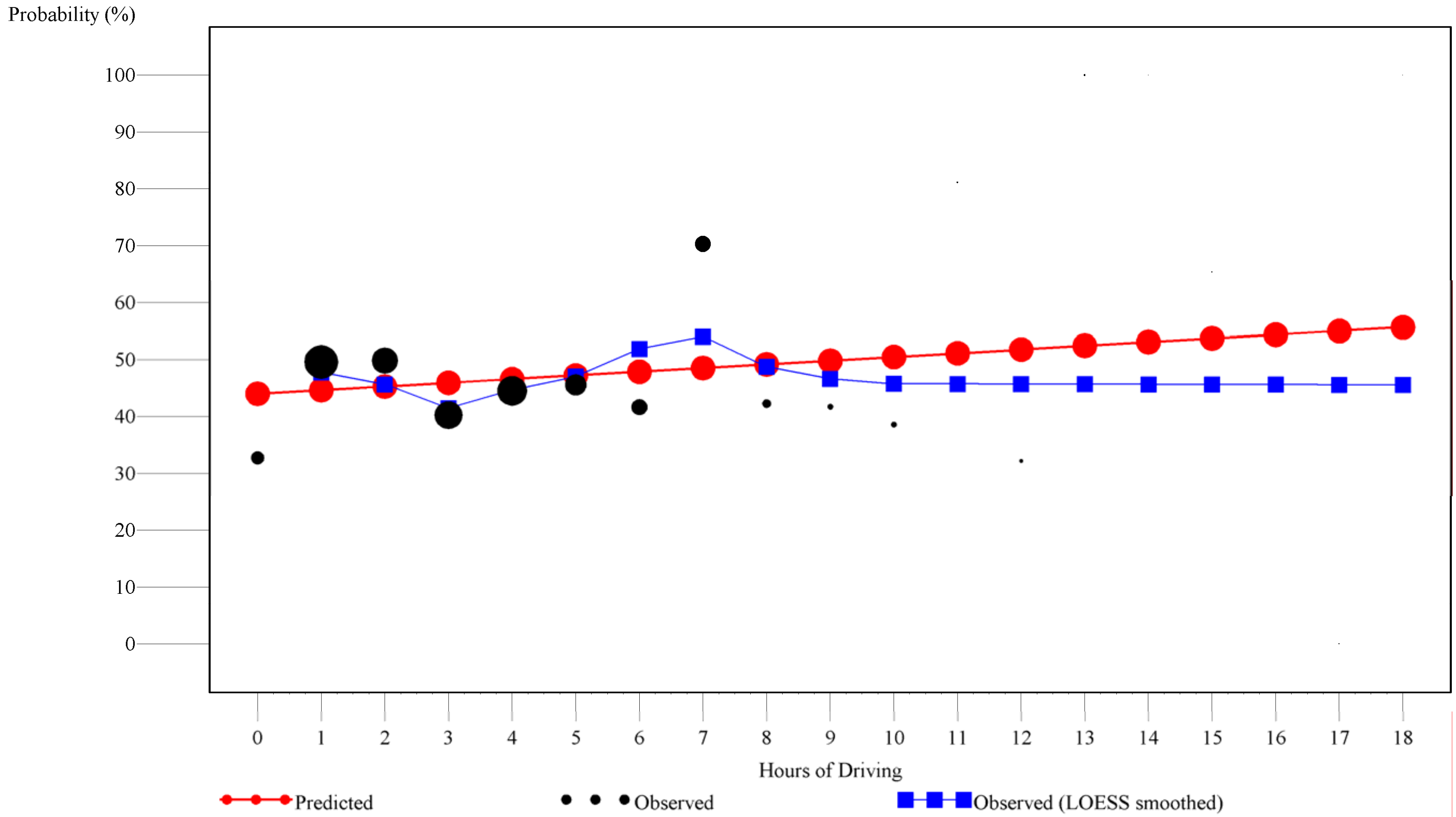


Figure 8. Probability of Driver Critical Responsibility given a crash as a function of Hours Worked On Day, Model with terms: Hours Worked on Day (linear).
Wald p-value for Hours Worked On Day = 0.98353
Size of black dot is proportional to total survey weight for observed value.

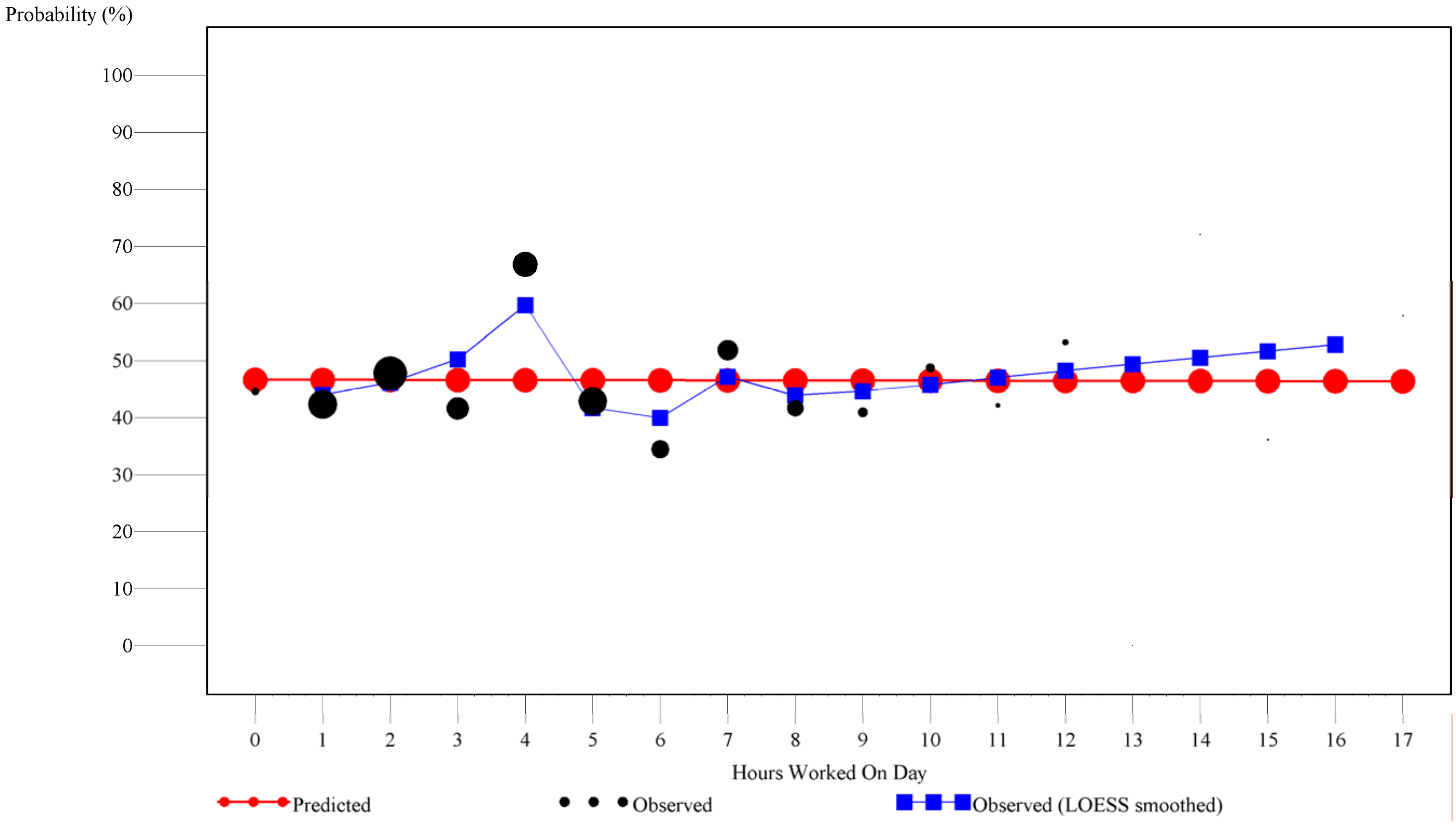


Figure 9. Probability of Driver Critical Responsibility given a crash as a function of Hours Awake, Model with terms: Hours Awake (quadratic). Wald p-value for Hours Awake = 0.08747

Size of black dot is proportional to total survey weight for observed value.

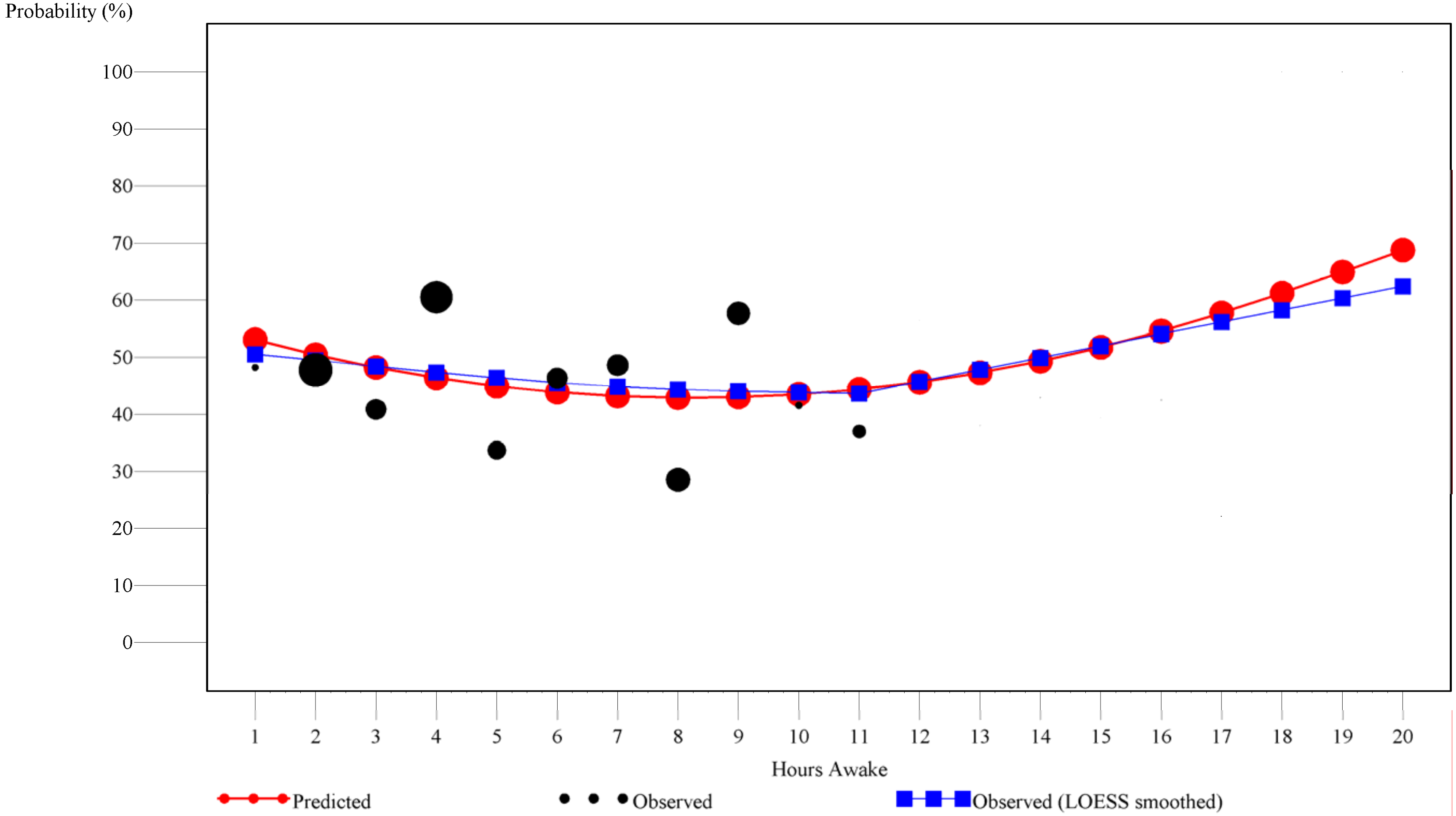


Figure 10. Probability of Driver Critical Responsibility given a crash as a function of Hours Slept,
Model with terms: Hours Slept (quadratic).
Wald p-value for Hours Slept = 0.07536
Size of black dot is proportional to total survey weight for observed value.

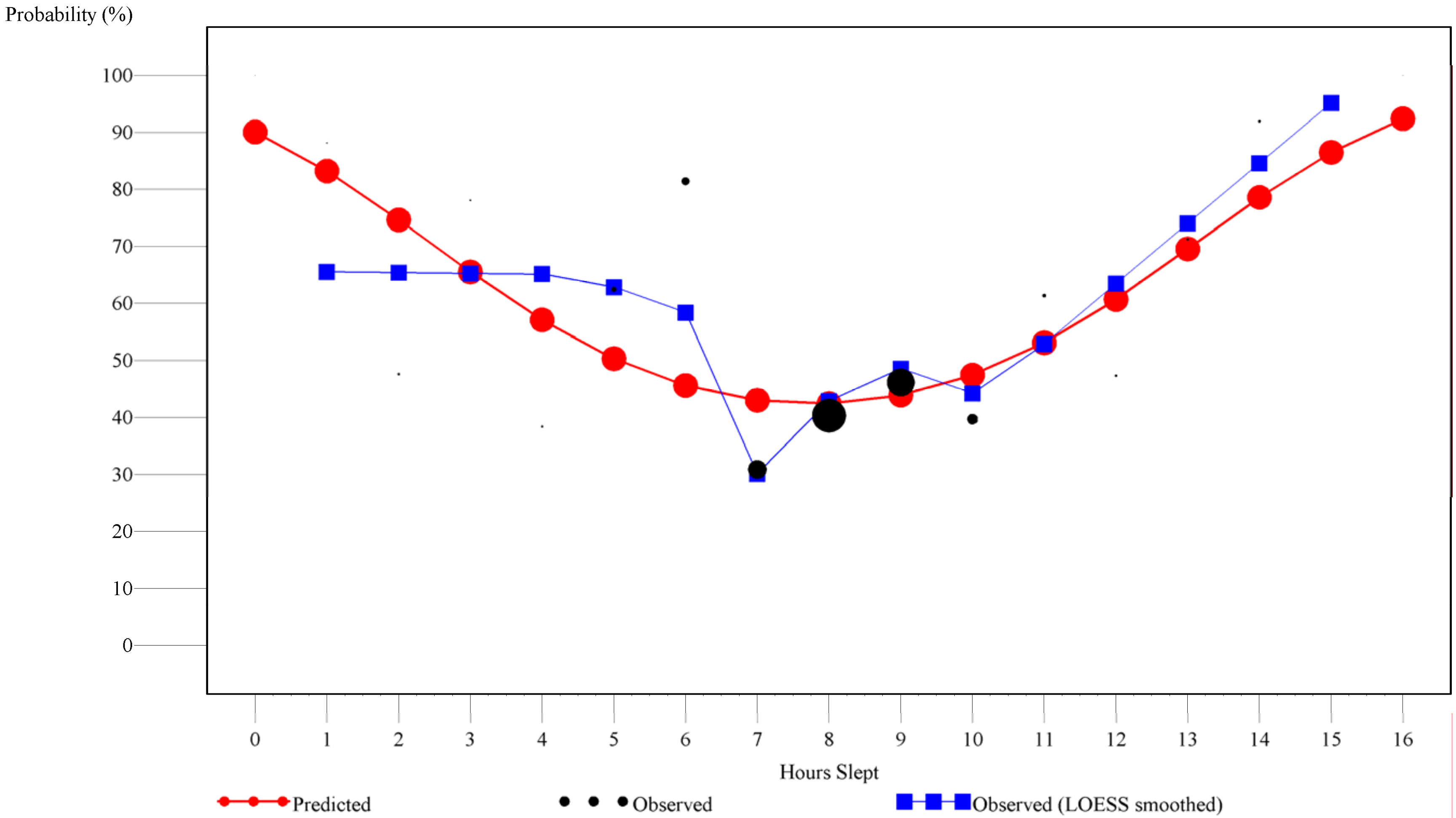
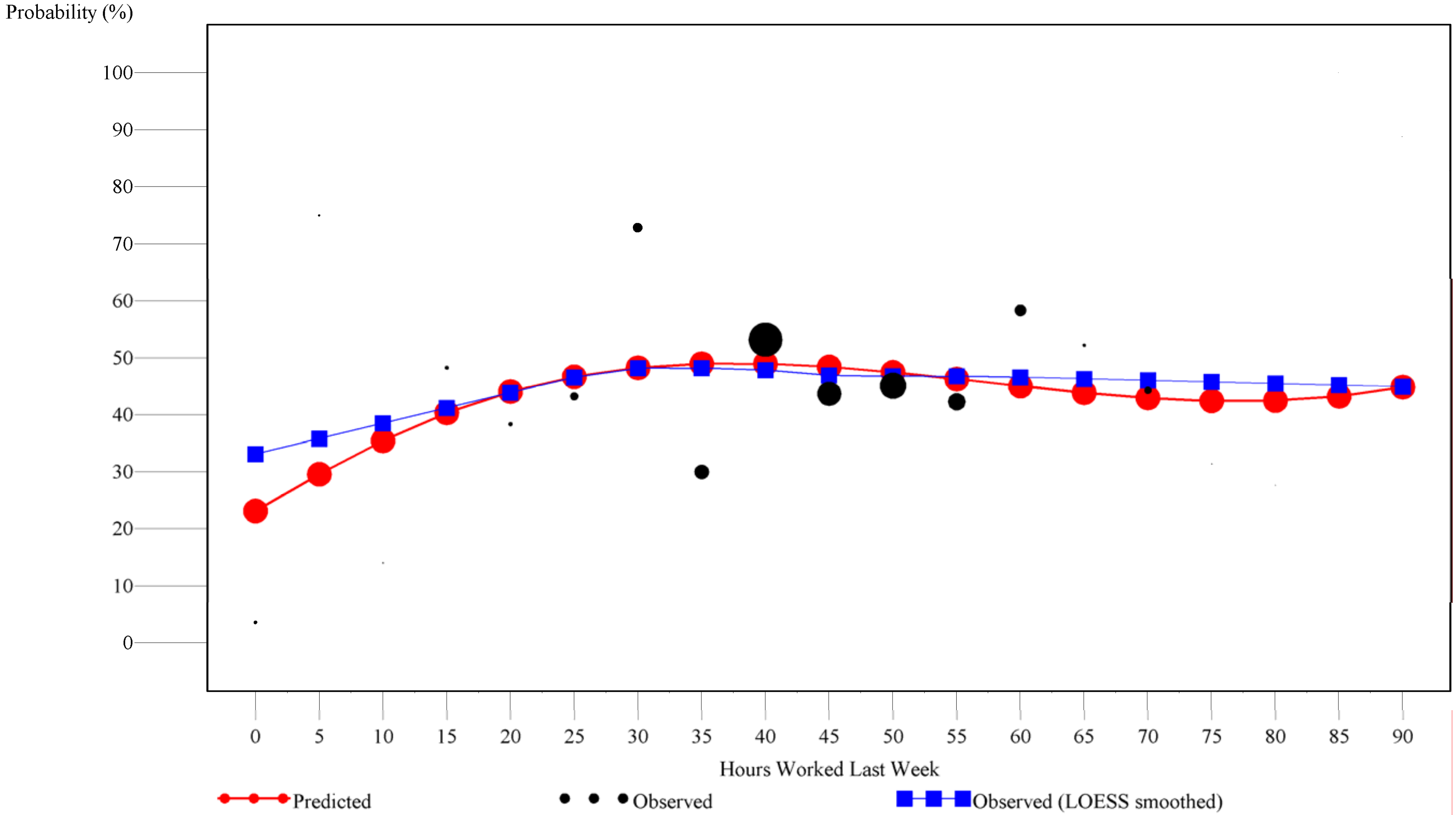


Figure 11. Probability of Driver Critical Responsibility given a crash as a function of Hours Worked Last Week,
Model with terms: Hours Worked Last Week (cubic).
Wald p-value for Hours Worked Last Week = 0.08624
Size of black dot is proportional to total survey weight for observed value.



We do not show here the detailed results for the driver critical responsibility models with terms in Time of Day, Vehicle Count, Day of Week, or Truck Type. The Time of Day model was not statistically significant (p-value 0.73). The Vehicle Count model showed a much higher probability for single vehicle crashes (predicted and observed probability 80 %) than for multiple vehicle crashes (predicted probability 35 %), and was statistically significant (p-value < 0.00001). The Day of Week model predicted a much lower driver critical responsibility probability on Saturday (27 % versus 49 % on Sunday and 47 % on weekdays), but was not statistically significant (p-value = 0.16). The Single Unit Trucks had a slightly higher driver critical responsibility probability (50 %) than the Combination Unit Trucks (46 %); the difference was borderline significant (p-value = 0.06).

We next used a stepwise approach to build up a multi-variable logistic model for driver critical responsibility. Each candidate model is a combination of one or more of the selected univariate models, so that for example, the Hours of Driving is assumed to have a linear effect, Hours Worked Last Week is assumed to have a cubic effect, and Vehicle Count is modeled categorically as single or multiple vehicle. At each step, the most significant term was added to the model if its Wald chi-square p-value was less than 0.10[7]. The least significant term was then subtracted from the model if its Wald chi-square p-value was 0.15 or greater. Just as for the driver fatigue model, we allowed a maximum of 9 degrees of freedom plus an intercept. The main effects model included the following terms, in order of their selection: Single Vehicle, Hours Sleep, Truck Type, and Hours Worked Last Week.

After building up the main effects model, we continued our process by adding and subtracting interaction terms in the same stepwise manner, where the candidate interaction terms are interactions between any of the four selected univariate terms in the main model. All the main effects terms remain in the model. The final model included the main effects listed above plus the interaction term Hours Sleep × Single Vehicle. This means that the quadratic effect of Hours Sleep is different for single and multiple vehicle crashes. Because of the interaction term, the predicted change in the logit (i.e., the log odds of driver fatigue) when Hours Sleep changes from a hours to b hours will be different for single and multiple vehicle crashes. The predicted driver fatigue probability and changes in that probability will depend upon all the explanatory variables. The coefficients of the model, standard errors, Wald chi-square statistics, and p-values are shown in Table 6. Recall, from Table 1, that singlev = 1 for single vehicle crashes, singlev = 2 for multiple vehicle crashes, typenum = 1 for SUT trucks, and typenum = 2 for CUT trucks.

[7] The last term added to the main effects model was Hours Worked Last Week. The p-value for this term was actually 0.1004 so that strictly following the stepwise procedure would exclude this term. However, since the p-value was so close to the nominal 10 % level for adding in a term, we chose to include it.

Table 6. Final driver critical responsibility model coefficients.

Variable	Value	DF	Estimate	StdErr	WaldChiSq	ProbChiSq
Intercept		1	-0.39923	0.30	1.74	0.1872
sleep		1	-0.54678	0.21	7.07	0.0078
sleep2		1	0.04014	0.02	7.11	0.0077
last		1	0.10748	0.05	5.35	0.0207
last2		1	-0.00232	0.00	3.05	0.0806
last3		1	0.00001	0.00	1.79	0.1807
singlev	1	1	8.30317	2.23	13.93	0.0002
singlev	2	0	0.00000			
typenum	1	1	0.33510	0.12	7.33	0.0068
typenum	2	0	0.00000			
sleep*singlev	1	1	-1.32348	0.54	5.96	0.0147
sleep*singlev	2	0	0.00000			
sleep2*singlev	1	1	0.06474	0.03	4.02	0.0450
sleep2*singlev	2	0	0.00000			

The p-values in Table 6 are for individual terms and estimate the statistical significance for testing that the individual coefficient is zero. For example, the p-value for the linear sleep term, keeping the quadratic term in the model, is 0.0078, and the p-value for singlev = 1, keeping the interaction terms in the model, is 0.0002. More useful is the p-value for each effect as a whole, given in Table 7.

Table 7. P-values for effects in final driver critical responsibility model.

Effect	P-Value
Hours Sleep (including interaction)*	2.09E-16
Single Vehicle (including interaction)*	9.78E-44
Hours Worked Last Week	0.0868
Truck Type	0.0068
Hours Sleep × Single Vehicle	0.0280

* This p-value tests that both the main effect and the interaction term are zero. Testing that the main effect is zero when an interaction term including that effect is in the model is usually not very meaningful.

Since the final model includes four main effects, the estimated driver critical responsibility probabilities depend upon the values of all those variables: Hours Sleep, Single Vehicle, Hours Worked Last Week, and Truck Type. To compare the predictions of the final driver critical responsibility model with the predictions of the univariate models (e.g., Figures 6-11) , we computed predictive marginals. The results (not shown) show very similar predictions to the univariate models.

COMPARE EFFECTS ON DRIVER FATIGUE AND CRITICAL RESPONSIBILITY

We can summarize these analyses by comparing how certain variables affect driver fatigue and critical responsibility. Figures 12 to 14 show the observed proportions of driver fatigue and driver critical responsibility for different values of Hours Sleep (rounded to the nearest hour), Hours of Driving (rounded to the nearest hour), and Hours Worked Last Week (rounded to the nearest 5 hours), respectively. The size of each bubble is proportional to the total survey weight.

Figure 12 shows that Hours Sleep has broadly similar effects on both driver fatigue and driver critical responsibility. It was statistically significant for both univariate models and also appeared in both final models. The bulk of the data is for between 7 and 10 hours of sleep.

Figure 13 shows a slight increase in the probability of driver fatigue as Hours of Driving increases from 0 to 11 hours. In particular, the probability of driver fatigue increased from 25 % to 53 % as the Hours of Driving increased from 10 to 11 hours. However, the observed probability *decreased* to 32 % at 12 hours. Beyond 10 hours, there is very little data (3 % of the total survey weight for the data subset analyzed) and the pattern is inconsistent. Hours of Driving was statistically significant by itself in the logistic model for the probability of driver fatigue, but was not included in the final model, and was no longer significant when Hours Awake and the other final model variables were included in the model. The plot shows a broadly similar pattern for the effects of Hours of Driving on driver critical responsibility. However, using the logistic model, Hours of Driving did not show a statistically significant effect on driver critical responsibility and was not included in the final model for driver critical responsibility. The logistic regression models for driver fatigue show a stronger effect than for driver critical responsibility because the predicted effects on a logit scale are much greater when the probabilities are closer to zero or 1.

Figure 14 examines the effects of Hours Worked Last Week. It was statistically significant for both univariate models (i.e., for driver fatigue and driver critical responsibility) and also appeared in both final models. The bulk of the data is for between 35 and 60 hours worked last week.

The observed probability of driver fatigue increases with hours worked last week up to a full work week of 40 hours, remains constant from 40 to 60 hours, drops slightly from 60 to 65 hours, and then tends to increase beyond 65 hours, although the available data after 60 hours have low survey weights. The logistic model (see Figure 5) with a linear term in Hours Worked Last Week predicts that the probability of driver fatigue increases with hours worked.

Figure 12. Probability of Driver Fatigue or Driver Critical Responsibility given a crash versus Hours Slept

Bubble size is proportional to total survey weight.

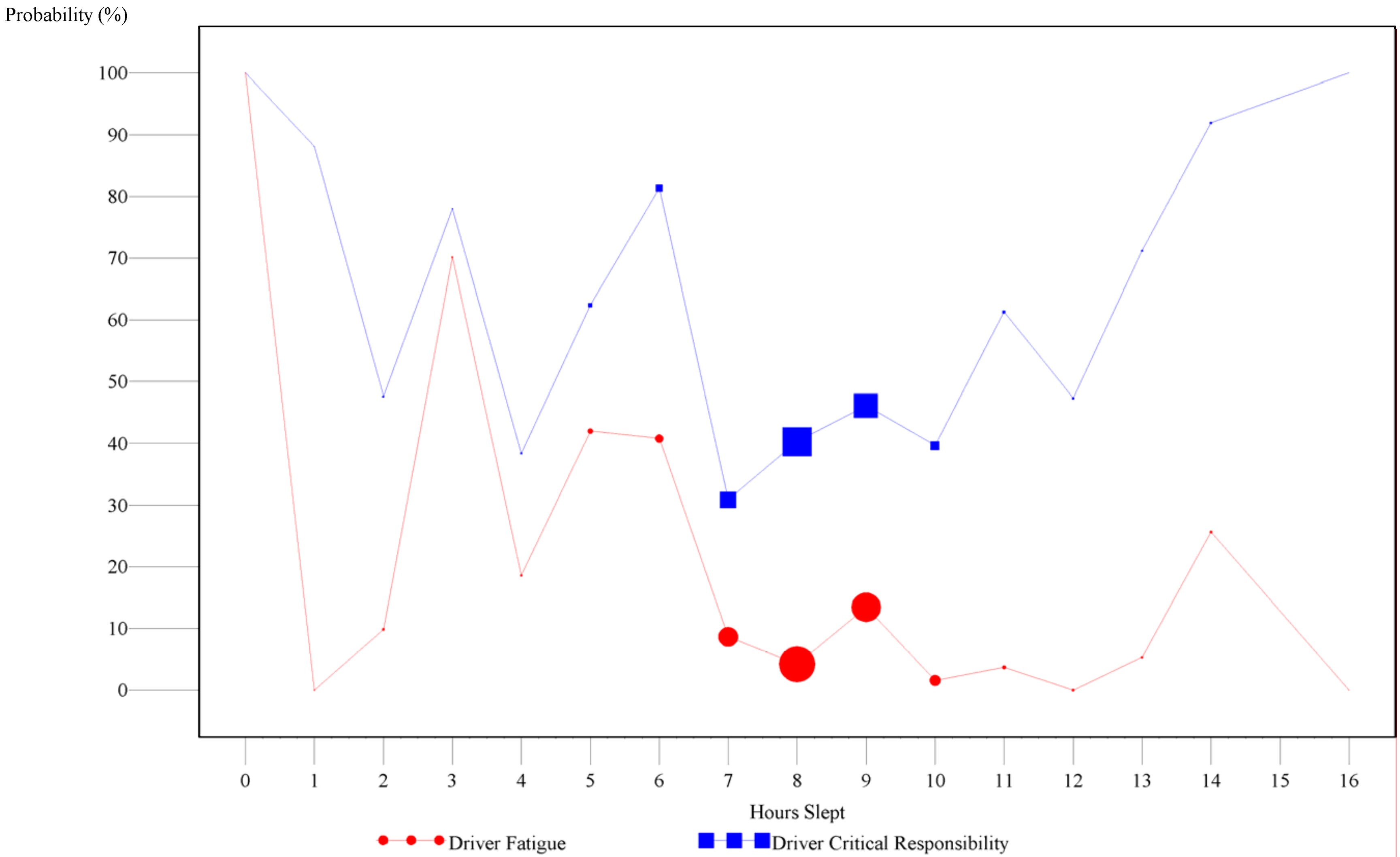


Figure 13. Probability of Driver Fatigue or Driver Critical Responsibility given a crash versus Hours of Driving

Bubble size is proportional to total survey weight.

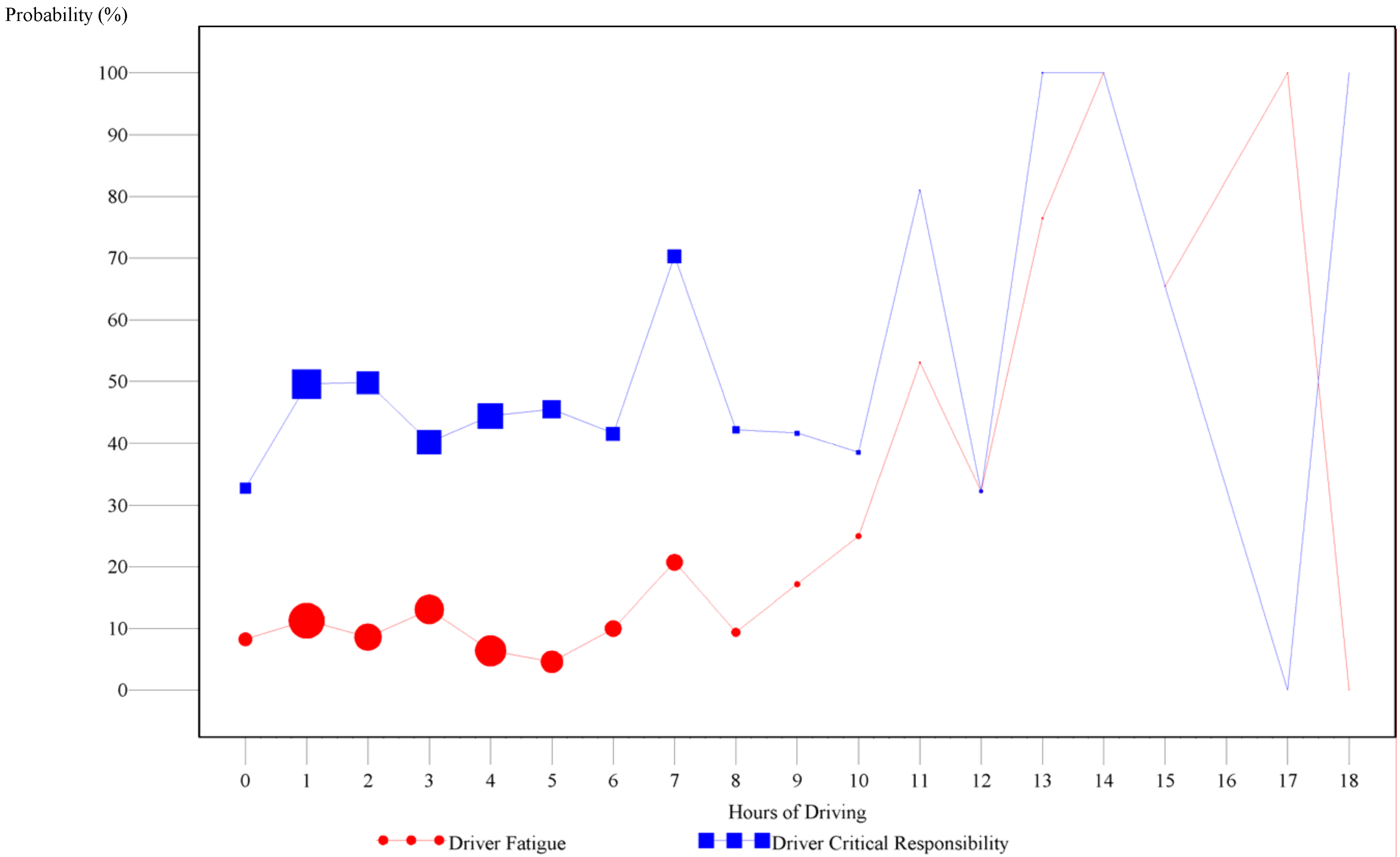
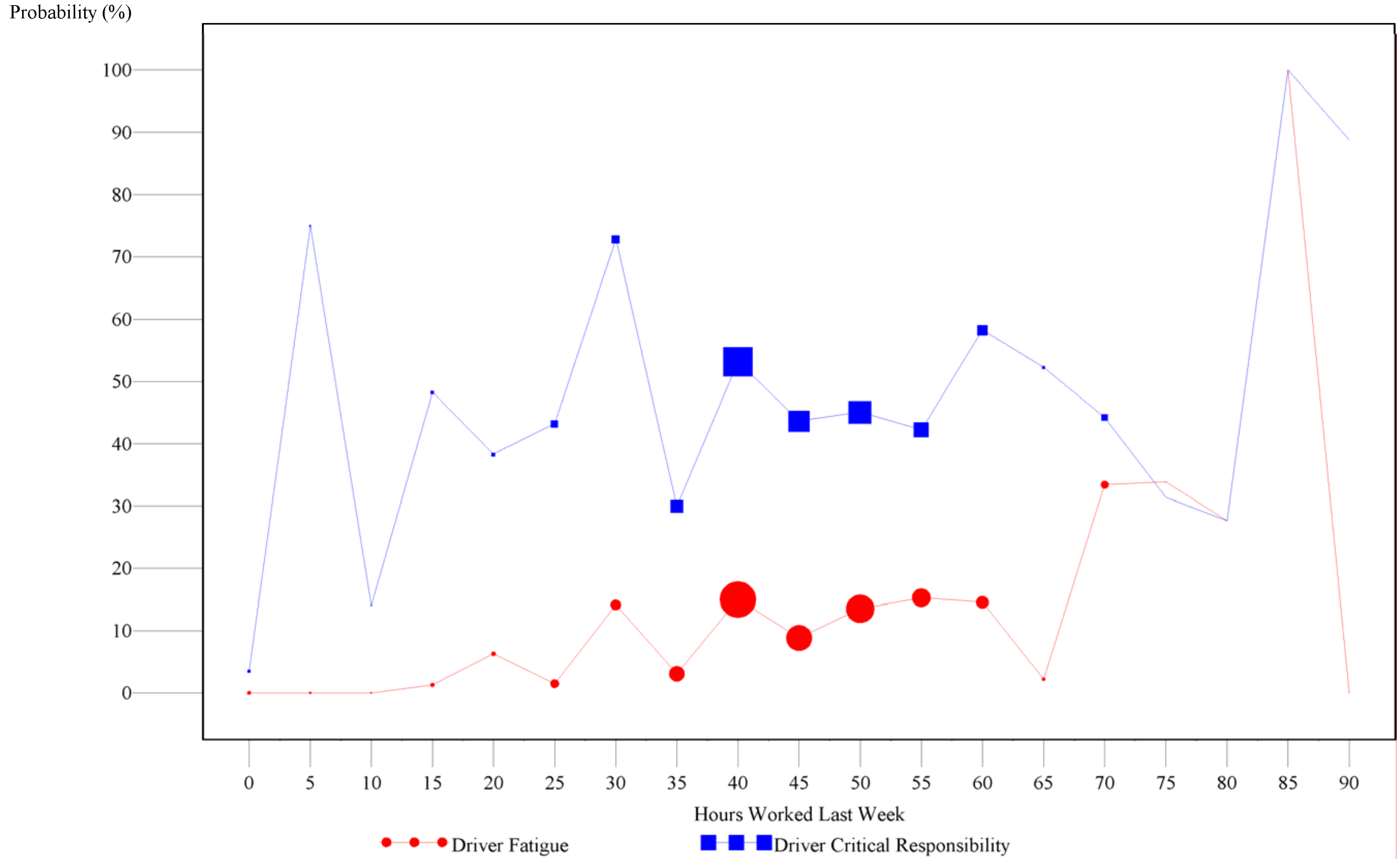


Figure 14. Probability of Driver Fatigue or Driver Critical Responsibility given a crash versus Hours Worked Last Week
Bubble size is proportional to total survey weight.



In Figure 14, the observed probability of driver critical responsibility as a function of Hours Worked Last Week is much more scattered than for driver fatigue. The probability tends to increase for hours worked up to 40 hours, remain constant from 40 to 60 hours, and then drops from 60 to 80 hours. The logistic model (see Figure 11) with a cubic term in Hours Worked Last Week predicts that the probability of driver fatigue increases with hours worked up to 40 hours, after which there is a slight decrease. However there is very little data for high values of Hours Worked Last Week.

Another approach to examining the effects of Hours Worked Last Week is to consider the effects of Average Hours Slept Last Week, which presumably will increase if Hours Worked Last Week decreases, and vice versa. We examine that issue in the following section.

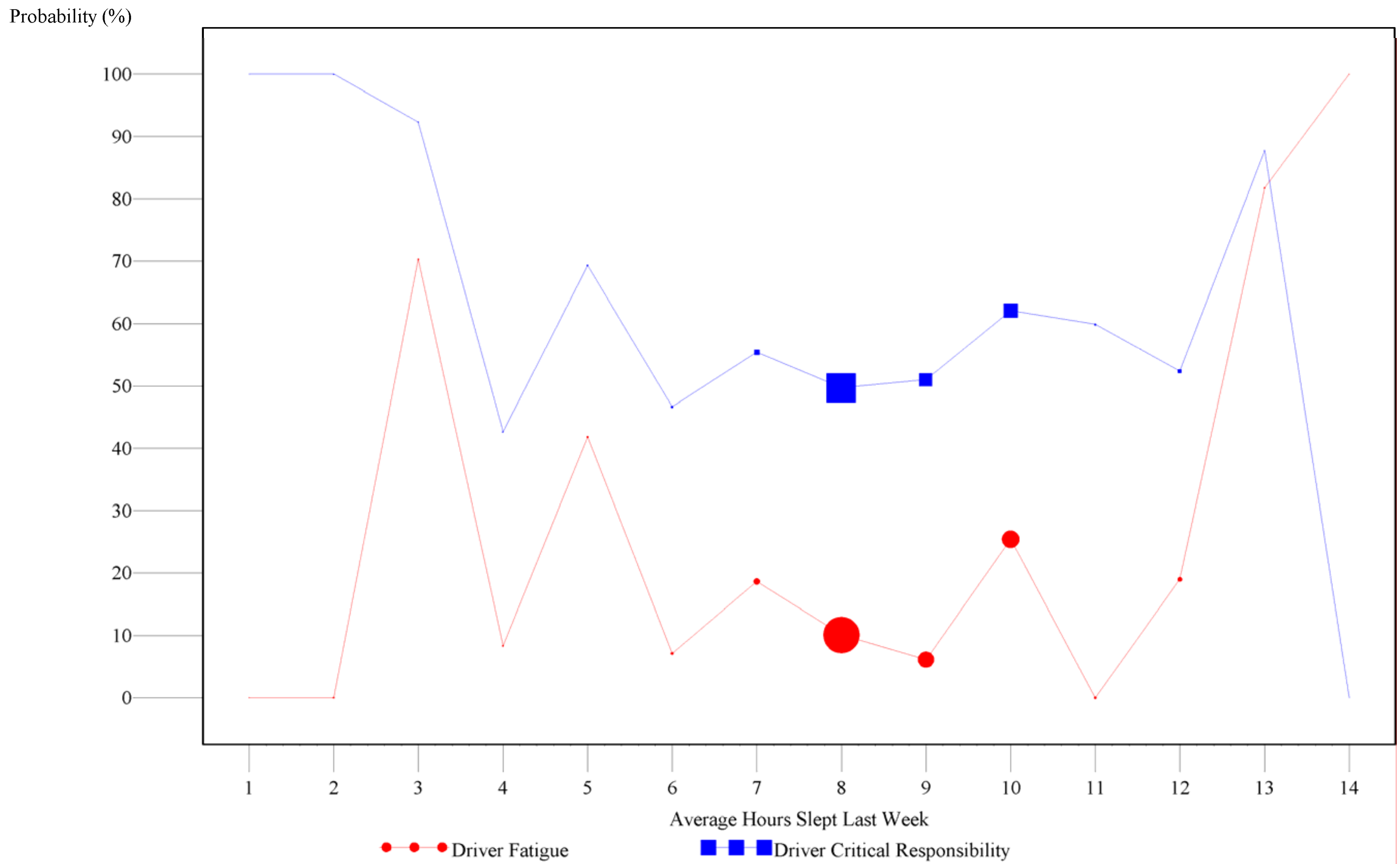
MODELS WITH AVERAGE HOURS SLEPT LAST WEEK

The LTCCS database also includes the variable AverageDay giving the average number of hours slept in the 7 days preceding the crash, i.e., the average of the daily hours slept. We shall call this variable “Average Hours Slept Last Week.” We would expect this variable to be related to driver fatigue and therefore to driver critical responsibility. However, many of the values for this variable are missing, and so adding this variable to the previous data set reduced the set of complete driver records from 706 to only 428 and reduced the number of clusters from 23 to 22. Due to this loss of data, we decided not to use this variable in the main analysis described above, but in this section we summarize the results of a revised analyses using Average Hours Slept Last Week as another explanatory variable with the smaller database.

Figure 15 shows the observed probabilities of driver fatigue and driver critical responsibility versus the Average Hours Slept Last Week, rounded to the nearest hour. Most of the survey-weighted data are for 7 to 10 hours. The curves are broadly similar, showing a steep decline from 3 to 8 or 9 hours, followed by a rapid rise.

We fitted univariate and multivariate logistic regression models in a similar manner to the main analyses. The preliminary logistic modeling suggested that Average Hours Slept Last Week should be modeled as a quadratic function both for driver fatigue and driver critical responsibility. The univariate formulations for several of the other explanatory variables also changed due to the smaller dataset. The selected formulations for the driver fatigue model were: Hours of Driving (quadratic), Hours Worked on Day (quadratic), Hours Awake (quadratic), Hours Slept (cubic), and Hours Worked Last Week (linear). The selected formulations for the driver critical responsibility model were: Hours of Driving (quadratic), Hours Worked on Day (linear), Hours Awake (quadratic), Hours Slept (cubic), and Hours Worked Last Week (quadratic).

Figure 15. Probability of Driver Fatigue or Driver Critical Responsibility given a crash versus Average Hours Slept Last Week
Bubble size is proportional to total survey weight.



Using the same stepwise logistic regression approach, we built up new models for the probabilities of driver fatigue and driver critical responsibility. For the probability of driver fatigue, the final model included the following terms, in order of their selection: Hours Awake, Hours Sleep, Single Vehicle, Hours of Driving, Hours Worked Last Week, and Average Hours Slept Last Week. (Although the last term increased the model degrees of freedom to 12, including the intercept, we chose to include the Average Hours Slept Last Week term in order to investigate its effects.) For the probability of driver critical responsibility, the final model included the following terms, in order of their selection: Hours Sleep, Single Vehicle, Average Hours Slept Last Week, Hours Worked on Day, and Hours Worked Last Week.

Figures 16 and 17 show the predicted marginals of Average Hours Slept Last Week in the final models for the probabilities of driver fatigue and driver critical responsibility. The predicted probabilities both decline rapidly from 0 to 10 hours and then slowly increase beyond 10 hours.

The final driver fatigue model included the quadratic effect of Hours of Driving. The predicted marginal probabilities are shown in Figure 18. The predicted probabilities slowly decline from 0 to 7 hours, slowly increase from 7 to 12 hours, and then increase more rapidly beyond 12 hours. There is a very small increase in the probability of driver fatigue from 10 to 11 Hours of Driving. Hours of Driving appears not to be associated with driver critical responsibility (p-value for univariate model = 0.22).

The effects of Hours Slept (not shown) and Hours Worked Last Week (shown in Figure 19) on the predicted probability of driver fatigue using the reduced data set are very similar to those found in the original modeling. Figure 19 shows that Hours Worked Last Week has a significant effect on the probability of driver fatigue even if the model already includes the Average Hours Slept Last Week. This holds even though the two explanatory variables are associated because increases in the hours of work imply fewer available hours for sleep. With both terms in the model, the coefficient for the linear effect of Hours Worked Last Week was 0.0425. Without the Average Hours Slept Last Week, the coefficient for the linear effect of Hours Worked Last Week was almost the same, 0.0381.

The effects of Hours Slept on the predicted probability of driver critical responsibility using the reduced data set (not shown) show the predicted probability decreases from about 65 % at 0 hours to 50 % at 7 hours and then increases to nearly 100 % at 15 hours. The effects of Hours Worked Last Week on the probability of driver critical responsibility using the reduced data set (not shown) show the predicted probability increases as the hours worked last week increases to about 40 hours, and then decreases after 40 hours.

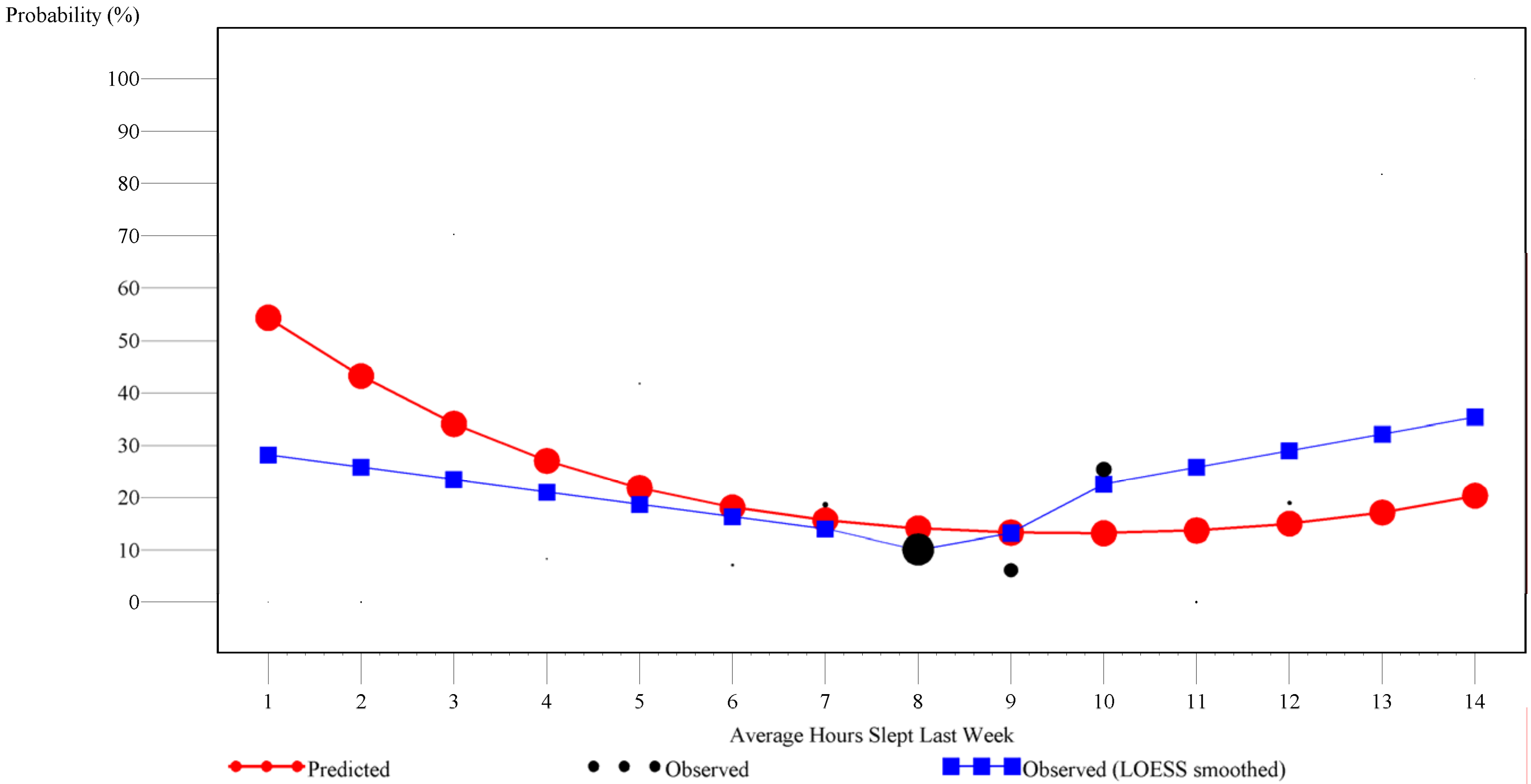
The effects of Hours Worked on Day on the predicted marginal probability of driver critical responsibility using the reduced data set are shown in Figure 20. The plot shows that the predicted probability slowly increases as the Hours Worked On Day increases.

Figure 16. Probability of being fatigued given a crash as a function of Average Hours Slept Last Week, Final model.

Wald p-value for overall model = 0.00000

Wald p-value for Average Hours Slept Last Week = 0.01201

Size of black dot is proportional to total survey weight for observed value.



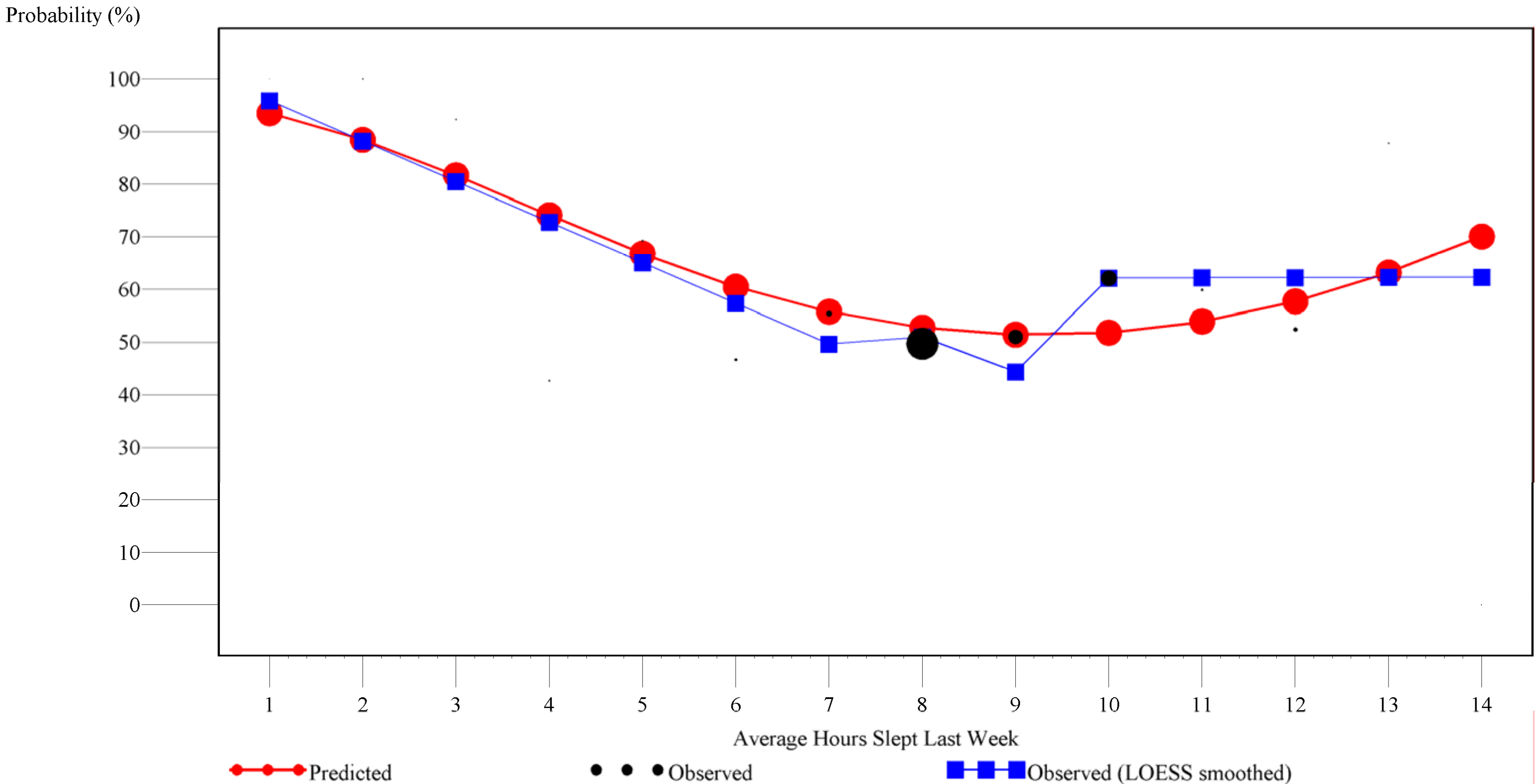
Model terms are: Hours Slept (cubic), Hours Awake (quadratic), Hours Worked Last Week (linear), Hours of Driving (quadratic), Average Hours Slept Last Week (quadratic), Single Vehicle

Figure 17. Probability of Driver Critical Responsibility given a crash as a function of Average Hours Slept Last Week, Final model.

Wald p-value for overall model = 0.00000

Wald p-value for Average Hours Slept Last Week = 0.00268

Size of black dot is proportional to total survey weight for observed value.



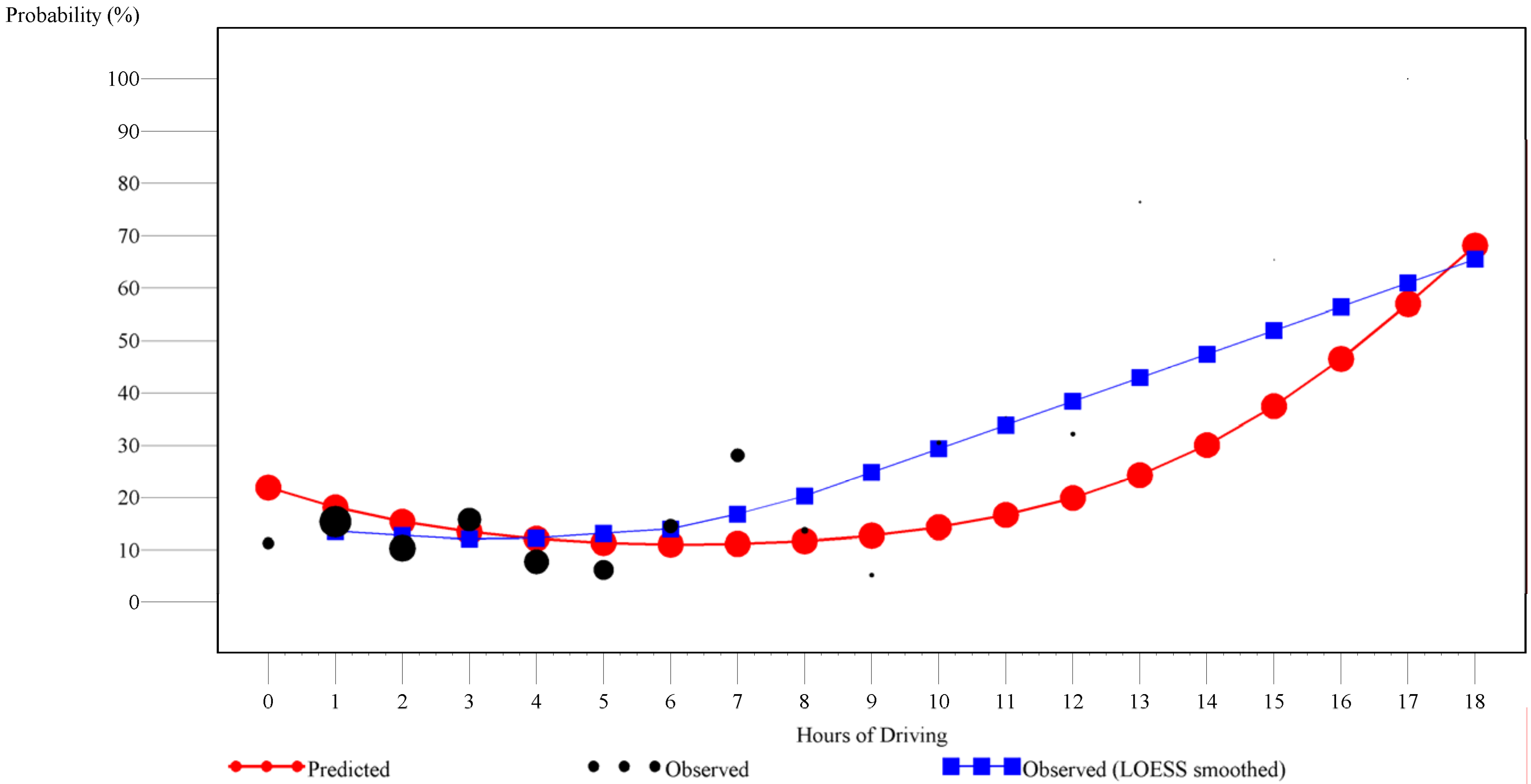
Model terms are: Hours Slept (cubic), Hours Worked Last Week (quadratic), Single Vehicle, Average Hours Slept Last Week (quadratic), Hours Worked on Day (linear)

Figure 18. Probability of being fatigued given a crash as a function of Hours of Driving, Final model.

Wald p-value for overall model = 0.00000

Wald p-value for Hours of Driving = 0.00361

Size of black dot is proportional to total survey weight for observed value.



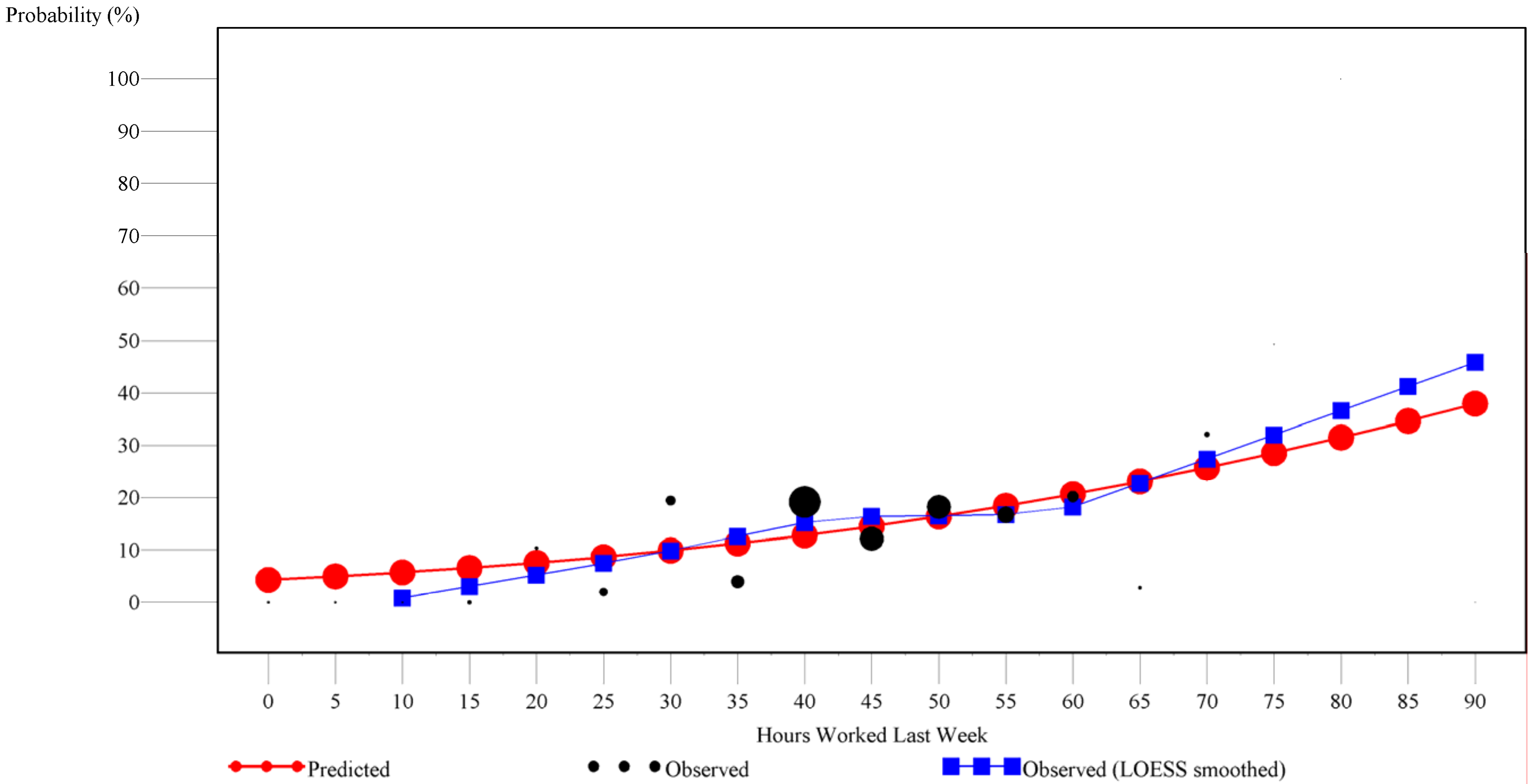
Model terms are: Hours Slept (cubic), Hours Awake (quadratic), Hours Worked Last Week (linear), Hours of Driving (quadratic), Average Hours Slept Last Week (quadratic), Single Vehicle

Figure 19. Probability of being fatigued given a crash as a function of Hours Worked Last Week, Final model.

Wald p-value for overall model = 0.00000

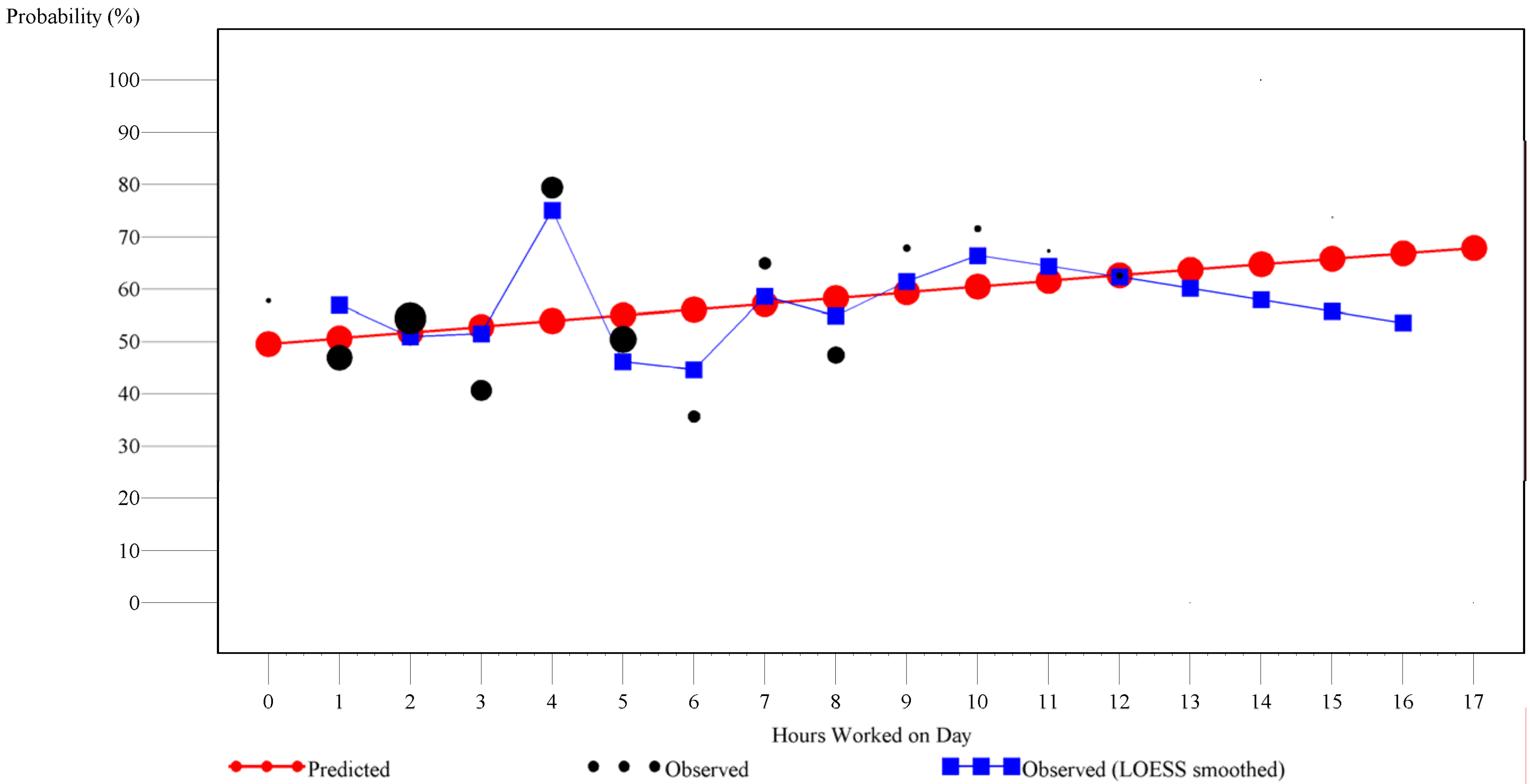
Wald p-value for Hours Worked Last Week = 0.01017

Size of black dot is proportional to total survey weight for observed value.



Model terms are: Hours Slept (cubic), Hours Awake (quadratic), Hours Worked Last Week (linear), Hours of Driving (quadratic), Average Hours Slept Last Week (quadratic), Single Vehicle

Figure 20. Probability of Driver Critical Responsibility given a crash as a function of Hours Worked on Day, Final model.
Wald p-value for overall model = 0.00000
Wald p-value for Hours Worked on Day = 0.00739
Size of black dot is proportional to total survey weight for observed value.



Model terms are: Hours Slept (cubic), Hours Worked Last Week (quadratic), Single Vehicle, Average Hours Slept Last Week (quadratic), Hours Worked on Day (linear)

CONCLUSION

This data set makes it possible to explore several important issues related to fatigue, working and sleeping schedules, and responsibility for crashes that are impossible with more limited data. Among the more striking findings are that sleep-related variables (including time awake, length of last sleep, and average sleep over the past week) are clearly related both to the chance that a large truck driver involved in a crash was fatigued and to the chance that the driver's actions made a crash inevitable. At the same time, though driving extra long hours in a day or working overtime the previous week appeared to increase fatigue, there was no evidence that they increased the chance that a driver's actions made a crash inevitable – that estimated probability was almost constant at the longer hours.

The major difficulty with this data set is that the determination of fatigue and the assignment of critical reason were both made somewhat subjectively by the LTCCS Researchers, Case Reviewers, and State truck inspectors from the available data and observations. So to some extent these statistical relationships only reflect these researchers', case reviewers', and inspectors' subjective, albeit educated, decision functions. In particular, driver fatigue was determined subjectively based on drivers' statements, the driver's sleep and work schedules, the observations of LTCCS researchers, case reviewers, inspectors, and witnesses, as well as crash scene diagrams, and not physiologically, so one should expect to find a relationship between the coding of fatigue and these variables. In the main model, long hours of driving in a day did not appear to be related even to fatigue once hours awake and hours worked were taken into account. If hours of work and hours awake are the explanatory variables of interest, not long driving times, then the use of data sets like TIFA would not be appropriate.