COMPREHENSIVE ANALYSIS OF WRONG-WAY DRIVING CRASHES ON ALABAMA INTERSTATES

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ABSTRACT

Crash data on Alabama Interstates were collected across a five-year time period from 2009 to 2013, and true wrong-way driving (WWD) crashes were identified using the hardcopy of crash reports and existing maps. The crash data contained 18 explanatory variables representing the driver, temporal, vehicle, and environmental information. A Firth's penalized-likelihood logistic regression model was developed to examine the influence of the explanatory variable on the dichotomous dependent variable (type of crash, i.e., WWD vs. non-WWD). This model is an appropriate tool to control the influence of all confounding variables on the probability of WWD crashes while considering the rareness of the event (i.e., WWD). A separate model using the standard binary logistic regression was also developed. Two information criteria (AIC and BIC) obtained from both developed models indicate that for our database, Firth's model outperforms the standard binary logistic model and provides more reliable results. Using Firth's model, explanatory variables including month of the year, time of the day, driver age, driver mental and physical condition, driver's residency distance, vehicle age, vehicle damage, towing condition, airbag deployment status, and roadway condition were found to characterize WWD crashes. Based on the obtained odds ratio (OR), this paper discusses the various effect of the identified variables and recommends several countermeasures for policy makers in order to reduce the WWD issue on Alabama Interstates.

Keywords: Wrong-way driving (WWD), Interstate highways, Statistical characteristics, Firth's penalized-likelihood logistic regression model, Model comparison

INTRODUCTION

While some crash types gain increasing attention due to their prevalence (e.g., run-off-the-road and intersection-related crashes), wrong-way driving (WWD) crashes receive special emphasis due more to their severity than to their frequency. This type of crash can occur on any one-way roadway; however, the concentration of most studies has been on controlled-access highways (i.e., freeways, expressways, and Interstate highways) as the speed limit is relatively high and – given the manner of the WWD crash, which is mostly head-on or opposite-direction sideswipe − the resulting outcome would be more severe (*1*).

To obtain a better understanding of the importance of the problem, the Fatality Analysis Reporting System (FARS) database was used to identify WWD crashes within a ten-year period (2004-2013) throughout the United States (U.S.) (*2*). An average of 265 fatal WWD crashes occurred per year on U.S. controlled-access highways, in which 355 people perished, resulting in almost 1.34 fatalities per WWD fatal crash. The significance of these kinds of crashes is corroborated when this number is compared to the fatalities per fatal crash rate of 1.10 for all other crash types, which translates to 24 more fatalities per 100 fatal crashes for WWD crashes than for fatal crashes in general. Given this evidence, it becomes necessary to identify the factors that best describe the WWD crashes and improve our knowledge of the underlying factors involved in WWD occurrence.

The National Transportation Safety Board (NTSB) has asked the Office of Safety Operations of the Alabama Department of Transportation (ALDOT) to develop a comprehensive highway safety program that incorporates, at a minimum, the program elements outlined in the National Highway Traffic Safety Administration (NHTSA) Highway Safety Program Guidelines (H-12-46) with a special focus on WWD crashes. Therefore, the state of Alabama decided that an in-depth investigation of WWD crashes on Alabama Interstates could provide a better understanding of such events. The purpose of this study is to review these severe crashes in depth, to recognize the contributing factors, to delineate between WWD crashes and non-WWD on Interstates, and to provide safety countermeasures and recommendations based on the obtained results that are specific to Alabama.

The rest of this paper is organized as follows. A review of the existing literature is provided next. The data used as well as the procedure to identify and verify true WWD crashes is presented. The methodology used in this paper, Firth's model, and its difference from standard binary logistic model (hereinafter "binary model") is described. This model then is applied to our data and the parameter estimates and odds ratio (OR) are presented. Further, the same data was analyzed with binary model to make a comparison between these two models. Based on the obtained results, several safety countermeasures are proposed.

LITERATURE REVIEW

Numerous studies have documented, more empirically than statistically, the contributing factors regarding WWD crashes on controlled-access highways (e.g., Interstates). While these studies were rare before the 2000s, various researchers started to examine these factors in the early 2000s, especially in Texas and Illinois; however, this topic of safety has gained renewed attention in recent years in both the U.S. and other countries. Although the majority of these studies have tried to use simple descriptive statistics to identify general characteristics of WWD (e.g., see *3*−*6*), several studies have been more specific in the database used or the methodology developed.

In a recently published paper by Kemel (*7*), a database was used to identify 266 crashes that involved WW drivers from 2008 to 2012 on French divided highways, and their characteristics were compared to those of other crashes (22,120 crashes) on the same highways during the same time period. This empirical research was then followed by a binary model to make it possible to account for the effect of all the variables simultaneously. The results showed that rare, severe WWD crashes are more likely to occur during nighttime conditions (12-6 AM). Regarding the driver's age, this type of crash is more prevalent among drivers 65 and older, which is consistent with the findings of the majority of existing literature. Based on this study, other characteristics of WW drivers that contribute to their likelihood of becoming involved in a WWD crash were identified, including whether they are intoxicated, are local drivers (and not in-transit), and are driving passenger cars alone (without any passengers). However, the database only shows around 1.2% of events (266 WWD vs. 22,120 non-WWD crashes), which may bias the results of a binary model.

Zhou et al. (*8*) also collected and analyzed WWD crashes on Illinois freeways over a six-year time period from 2004 to 2009. In their study, WWD crashes were characterized based on three different aspects: the crash (e.g., temporal distribution, roadways characteristics), the vehicle (e.g., characteristics, operation), and the driver (e.g., age, condition). Their study showed that a large proportion of WWD crashes occurred during weekends from 12 to 5 AM. While nearly two-thirds of WW drivers were driving under the influence (DUI), the authors suggested that this number might be even higher as many drivers either refused to take the sobriety test or had no test results recorded in the reports. This study revealed that younger drivers (under 25) are also overrepresented just like older drivers (above 65). Other contributions of their study include a method to identify entry points and to rank different interchange types based on the rate of WWD entries and a guidebook (*9*).

Lathrop et al. (*10*) explored a 15-year dataset (1990-2004) for fatal crashes on New Mexico's Interstates. Their sample was composed of 875 fatal non-WWD crashes and 49 fatal crashes, which had resulted in 1,092 and 79 fatalities, respectively. Various characteristics of fatal WWD crashes, including decedent demographics, occupant status, safety equipment use, and roadway and environmental conditions, were compared to those of other non-WWD fatal crashes as a comparison group. Driver alcohol consumption was an affecting factor − accounting for 60% of WWD crashes − as was darkness. It was also identified that WWD vehicle occupants are less likely to be wearing their seatbelts during crashes, which intensifies crash severity.

Another non-U.S. study conducted by Xing (*11*) in Japan, analyzed the characteristics of both WWD crashes and incidents with an emphasis on crashes. In doing so, 4,769 WWD incidents and 133 WWD crashes over five years (2005-2009) were considered. This study's database has its advantage compared to that of other studies as it contains more records; however, its disadvantage is that it lacks interviews with WW drivers and therefore lacks other supplementary information. Other than confirming the findings of previous studies, the researcher sought to elaborate more on the application of Intelligent Transportation System (ITS) technologies, such as roadside WW navigation alert systems and WW warning systems with road-to-vehicle communication.

The literature review showed that most recent studies use simple descriptive statistics to identify contributing factors to WWD crashes. Few have focused on comparing WWD crashes with non-WWD crashes to test the significance of the identified contributing factors, which can be done using logistic regression models. There has been a myriad of previous research investigating the effect of several factors on one particular outcome in the field of traffic safety

using logistic regression models (*12−17*). In this paper, a new logistic method – Firth's penalized-likelihood logistic regression – is used to characterize WWD crashes while accounting for the effect of all confounding parameters. This method is a generalization of the maximum likelihood estimate (MLE) models. The advantage of this type of logistic regression model is that it can handle the bias in the calculations due to the small sample size and rareness of the event (which is the case in this study) satisfactorily. This method has specifically been used in medical science formerly. For example, Xu et al. (*18*) analyzed a sample size of 67 patients with just 28 patients developed hypertension, which is pretty small sample size for MLE method. In another study by Mulla et al. (*19*), they analyzed a sample of 138 patients with only 16 (11.6%) having preeclampsia, that may cause computational problems when being analyzed with MLE methods.

DATA

This study's approach to identifying WWD crashes is twofold: identifying possible WWD crashes and verifying true WWD crashes. The first step used pertinent variables to separate possible WWD crashes from the total crashes in the database. Afterwards, a hardcopy of the crash reports for each of these possible WWD crashes was reviewed carefully, and the true WWD crashes were identified based on crash narratives as well as diagrams and locations. Three variable categories – at the roadway, vehicle, and person levels – were used to define WWD movements in the crash database.

Wrong-Way Driving Identification

The statistical data source used in this study is the Alabama crash records database accessed through the Critical Analysis Reporting Environment, also known as CARE, software (*20*). This software is designed to help identify inherent statistical characteristics of various kinds of crashes from different perspectives, such as driver, roadway, and vehicle. This software also enables researchers to apply filters and extract specific kinds of crashes for further analysis, although WWD crashes cannot be directly extracted from the database. Therefore, it was necessary to define appropriate filters on variables to separate possible WWD crashes for further investigation based on the crash diagram, geographic coordinates, and narrative. All of the variables in the CARE system were reviewed, but only those that could help identify possible WWD crashes were investigated. This effort recognized contributing circumstances, maneuvers, and citations issued for either the crash, the causal unit (CU), or the second vehicle (V2), which may define any possible WWD movements on roadways. Table 1 summarizes the variables as well as the corresponding values used to identify possible WWD crashes for further examination.

This filter was then applied to Interstate, federal, and state highways in the hierarchy of highway classification in CARE, resulting in 132, 525, and 799 possible WWD crashes (1,456 altogether), respectively. The reason why this filter was also applied to federal and state highways (as non-Interstate highways) was that the preliminary research on WWD crashes revealed that some true WWD crashes happened on exit ramps were coded as crashes on non-Interstate highways (depending on the classification of the crossroad connected to the exit ramp).

Wrong-way Driving Verification

To verify the actual WWD incidents on Interstates and their access ramps, crash hardcopies for those 1,456 possible WWD crashes were requested from the ALDOT. The first step was to confirm that the crashes had occurred at the target locations. To this end, the crash diagrams

were checked, or in the case of no diagram, the crashes were located on Web map services, such as Google Maps.

TABLE 1 Summary of Variables and Their Values to Identify Possible WWD Crashes

Variable	Value(s)
Primary Contributing Circumstance	- Traveling Wrong Way/Wrong Side - Wrong Side of Road
CU Contributing Circumstance	- Traveling Wrong Way/Wrong Side - Wrong Side of Road
V2 Contributing Circumstance	- Traveling Wrong Way/Wrong Side - Wrong Side of Road
CU Vehicle Maneuvers	- Wrong Side of Road - Wrong Way on One Way
V2 Vehicle Maneuvers	- Wrong Side of Road - Wrong Way on One Way
CU Citation Issued	- Wrong Side of Road
V2 Citation Issued	- Wrong Side of Road

The next step was to review the narrative description for all the remaining crash reports in order to confirm that each crash was truly the result of a WWD maneuver. The actual WWD crashes were confirmed with respect to key phrases in the narratives such as “traveling the wrong way”, “traveling northbound on the southbound lanes” or “turned right on the northbound exit ramp.” Altogether, 93 crashes were verified as true WWD crashes. Our investigation showed that the majority of unverified WWD crashes on Interstate highways were those that happened after a vehicle crossed the median and struck an oncoming vehicle immediately afterwards. For federal and state highways the majority were those driving on the wrong side of the road, as the code to nominate possible WWD crashes contains “wrong side” that inadvertently brings a lot of non-WWD crashes into the database.

Table 2 represents the total and fatal crashes for all Interstate and WWD crashes along with their percentage in Alabama from 2009 to 2013. As can be seen from this table, WWD crashes comprise less than 0.2% of Interstate crashes (indicating a rare event); however, almost 4% of all Interstate fatal crashes are due to WWD. Finally, a spreadsheet of crash data with rows (representing each crash record) and columns (representing each attribute in the crash record) was prepared for additional analysis.

TABLE 2 Number of Interstate and WWD Crashes

Year	**2009**	**2010**	**2011**	**2012**	**2013**	**Total**
Interstate Crashes	11,023	11,433	11,967	11,258	11,358	57,039
WWD Crashes	17	16	25	16	19	93
Percent	0.15%	0.14%	0.21%	0.14%	0.17%	0.16%
Interstate Fatal Crashes	64	79	76	73	69	361
WWD Fatal Crashes	4	2	4	2	2	14
Percent	6.3%	2.5%	5.3%	2.7%	2.9%	3.9%

Descriptive Statistics

The explanatory variables used in this study are cross-tabulated for both WWD and non-WWD crashes on Interstate highways and are presented in percentage in Table 3. It should be noted that the Other/Unknown categories for the variables are not presented in this table; therefore, the total number for some variables under the columns may not sum up to 100%. In addition, since the number of WWD crashes is less than 100, the percentages for this category are not reported to decimals. When looking at this table, a few points are worthy of mentioning. For example, 26% of WW drivers are older than 65 while this age group are responsible for 7.9% of other crashes. The share of DUI drivers is also considerably high such that almost half of the WW drivers were intoxicated. WWD crashes are also disproportionately more frequent during evening and night. Almost 80% of WWD crashes have happened during these time periods that may be reflective of the possible abnormal driving conditions (e.g., DUI, drowsy, fatigue).

TABLE 3 Descriptive Statistics Distribution of WWD and Non-WWD Crashes on Alabama Interstates

Explanatory Variable	Category	WWD Crashes (n=93)	Other Crashes (n=57,039)
Driver Age	Less than 24	18	25.7
	25 to 34 years	23	22.7
	35 to 44 years	15	16.3
	45 to 54 years	9	13.8
	55 to 64 years	4	9.3
	65 years of over	26	7.9
Driver Gender	Male	67	57.8
	Female	24	36.5
Driver Condition	Apparently Normal	25	84.5
	DUI	46	3.9
	Physical Impairment	4	0.1
	Asleep/Fainted/Fatigued	1	3
	Illness	1	0.4
Driver Residency Distance	Less than 25 Miles	59	48.9
	Greater than 25 Miles	28	44.2
Month of the Year	January	4	7.9
	February	9	7.8
	March	14	8.7
	April	3	7.6
	May	16	8.8
	June	7	8.4
	July	7	9.1
	August	4	8.1
	September	7	8
	October	7	8
	November	14	8.6
	December	10	9
Day of Week	Weekday	53	74.6
	Weekend	47	25.4
Time of the Day	Morning (6-12)	13	29.3
	Afternoon (12-18)	8	41.9

	Evening (18-24)	33	18.4
	Night (0-6)	46	10.3
Vehicle Age	Less than 5 years	16	25.7
	5 to 15 years	60	58.2
	More than 15 years	17	10.4
CU Vehicle Damage	Minor/None Visible	10	28.7
	Major Not Disabled	12	23.2
	Major and Disabled	70	44.4
Vehicle Towed?	No	15	49.5
	Yes	82	48.8
CU Driver Seatbelt Use	Belt Used	67	89.4
	Belt Not Used	9	2.1
CU Driver Airbag Status	Not Deployed	32	69.2
	Deployed	48	14.8
Setting	Rural	38	41.2
	Urban	62	58.8
Lighting Condition	Daylight	24	69.2
	Dark, Road Lit	27	9.8
	Dark, Road Not Lit	44	16.7
	Dawn	2	1.5
	Dusk	2	2.6
Weather Condition	Clear/Cloudy	90	77.9
	Fog/Mist	3	2.2
	Precipitation	7	19.6
Roadway Condition	Dry	90	72.3
	Wet	10	27.1

METHODOLOGY

Firth's Penalized-Likelihood Logistic Regression

The aim of this paper is to identify the explanatory variables that differentiate WWD crashes from other crashes on Interstates, which can be handled by the introduction of logistic regression analysis. Given the type of dependent variable in this study (WWD vs. non-WWD crashes), a binary logistic regression is suggested. When looking at the data, three conditions are visible: the rarity phenomenon, unbalanced data, and disproportionality of observations and explanatory variables. First, for the rareness of the events, only 0.16% of Interstate crashes are due to WWD. This rareness of events in binary logistic regression is known to be especially difficult to explain and predict. Furthermore, most well-known statistical analysis methods, e.g., binary logistic regression, can be heavily affected by this phenomenon and, consequently, the probability of the rare event will be sharply underestimated (*21*). Second, some categories for WWD crashes have very low frequency, which can cause problems in computations (*22*). Third, statistical guidelines recommend having at least 10 observations per each explanatory variable in order to make the model and calculate the parameter estimates (*23*). These issues might limit the applicability of the standard logistic regression, as it uses the MLE, which is known to suffer from the small-sample bias. In this situation, a penalized-likelihood approach is proposed (i.e., Firth's logistic regression), which reduces the small-sample bias of the MLE method (*24* and *25*).

Firth (*24*) introduced a penalized MLE into the binary model that can offset the bias involved in MLE. As we know, in the binary model, the log-likelihood can be formulated as an exponential family model as follows:

$$l(\beta) = t\beta_n - K(\beta_n), \quad n = 1, \dots, k \tag{1}$$

where t is the vector of observed sufficient statistics, β_n is the regression parameter to be estimated, and k is the number of parameters estimated. However, the score (gradient) function, which is derivative of the log-likelihood, will be used to calculate the MLE of the parameter β_n as follows:

$$U(\beta_n) = l'(\beta_n) = t - K(\beta_n), \quad n = 1, \dots, k \tag{2}$$

To penalize the MLE, Firth replaced the score function of the binary model by a modified score function as follows:

$$U(\beta_n)^* = U(\beta_n) + \alpha_n, \quad n = 1, \dots, k \tag{3}$$

where α_n has the nth entry and is formulated as:

$$\alpha_n = \frac{1}{2} tr\left[I(\beta)^{-1} \frac{\partial I(\beta)}{\beta_n}\right], \quad n = 1, \dots, k \tag{4}$$

where *tr* is the trace function and $I(\beta)$ is the Fisher's information matrix, which is minus the second derivative of the log-likelihood. Using this method, the MLE estimate will be shrunk towards zero. It is believed that compared to the broad class of generalized linear models on small samples, Firth's method is precise in estimating coefficients and reliable in calculating confidence intervals in terms of coverage probabilities (*26*).

After calculating parameter estimates for statistically significant variables, the odds ratio (OR) as a relative measure of effect and the corresponding confidence interval (CI) were calculated. The OR can provide a better understanding of the direction and magnitude of the change in the probability of the dependent variable with one unit change in the specific variable. In other words, when OR is greater than one, the study group (here, WWD crashes) is more likely to have the specific characteristic (defined in the category) than the reference category. A similar explanation applies to OR of less than one.

Model Comparison

Given the difference in the score functions of the binary model and Firth's model, a comparison between the outputs of these two models can be made. In doing so, two popular information criteria (Akaike Information Criterion, or AIC, and Bayesian Information Criterion, or BIC) for comparing maximum likelihood models were used. The AIC and BIC can be formulated as follows:

$$AIC = -2LL_{Full} + 2k \tag{5}$$

$$BIC = -2LL_{Full} + \ln(N) \times k \tag{6}$$

where LL_{Full} is the (penalized) log-likelihood of the full model with statistically significant explanatory variables, k is the number of parameters estimated in the final model, and N is the number of observations (57,132 observations). In addition to comparing the model fit, these two measures can also account for the complexity of the model by penalizing the criterion for the number of explanatory variables included in the model. This penalization is carried out by either $2k$ or $\ln(N) \times k$ terms in the equations. Having the models fit on the same dataset, the model with lower AIC and BIC is considered to outperform the other.

RESULTS AND DISCUSSION

Previously, the descriptive statistics of the explanatory variables for each type of crash on Interstates were presented. In this section, these variables will be put into one model for multivariate analysis in order to identify the effect of the explanatory variables on the type of crash altogether. In doing so, Firth's model was found more appropriate than binary model given the nature of the data. The empirical results of this study are presented next. These results include the parameter estimates obtained from Firth's model and the interpretation of these estimates. Moreover, the same dataset was used to fit a binary model and the parameter estimates for this model is also presented. AIC and BIC values for both of these models are calculated and a comparison between these two models are made.

The R software package "logistf" was exploited as a comprehensive tool to estimate the effect of various contributing factors on the probability of WWD crashes (*27*). First, a model was fit with all possible contributing factors. Subsequently, a backward elimination procedure based on the penalized-likelihood ratio test (as is the suitable procedure for nested models) was employed to produce a final model that best explains the dependent variable. A forward selection process also yielded a similar result. Table 4 summarizes the analysis results of the Firth's model, including parameter estimates along with their corresponding standard errors, OR and corresponding 95% confidence intervals.

The analysis of the crash characteristics is performed by categorizing the information about each crash into four major groups – time information, responsible driver, vehicle information, and environmental condition. Each of these categories are discussed in the following subsections. The Wald chi-square statistic of 336.7 with 31 degrees of freedom, which is substantially larger than the respective chi-square values at any reasonable confidence level, demonstrates that the alternative hypothesis (i.e., "the current model is true") is accepted. Consequently, the explanatory variables given in the model affect the type of crash, or the model with independent variables is statistically better than the model with only the intercept (the null model).

The same data was used to develop a binary model and parameter estimates and ORs were calculated. Having these two models (Firth's model and binary model) on the same data, AIC and BIC were calculated using equations 5 and 6 and are presented in Table 4. As can be seen in this table, Firth's model yields lower values for both AIC and BIC, proving better fit compared to the binary model on our imbalanced data. Moreover, the standard error of parameter estimates are generally lower in Firth's model, indicating a more accurate model compared to the binary model.

TABLE 4 Final Firth's and Binary Model Results

Explanatory Variable	Firth's Model			Standard Binary Logistic Model		
	β	S.E.	OR (95% CI)	β	S.E.	OR (95% CI)
Month of the Year						
January	–	–	Reference	–	–	Reference
February	0.76	0.60	2.15 (0.66; 6.96)	0.82	0.63	2.27 (0.66; 7.81)
March	1.16*	0.56	3.19 (1.06; 9.65)	1.24*	0.59	3.47 (1.09; 11.06)
April	-0.27	0.73	0.76 (0.18; 3.19)	-0.32	0.78	0.73 (0.16; 3.38)
May	1.24*	0.56	3.47 (1.16; 10.37)	1.33*	0.59	3.80 (1.2; 11.96)
June	0.46	0.63	1.58 (0.46; 5.44)	0.49	0.66	1.64 (0.45; 6.03)
July	0.55	0.63	1.73 (0.5; 5.96)	0.59	0.66	1.80 (0.49; 6.59)
August	0.19	0.68	1.21 (0.32; 4.63)	0.19	0.72	1.21 (0.29; 5)
September	0.40	0.64	1.49 (0.43; 5.16)	0.44	0.67	1.55 (0.42; 5.72)
October	0.39	0.63	1.48 (0.43; 5.09)	0.43	0.66	1.53 (0.42; 5.63)
November	1.27*	0.56	3.56 (1.18; 10.74)	1.36*	0.59	3.88 (1.22; 12.35)
December	0.85	0.59	2.35 (0.74; 7.45)	0.92	0.62	2.51 (0.75; 8.42)
Time of the Day						
Morning (6-12)	–	–	Reference	–	–	Reference
Afternoon (12-18)	-0.79	0.47	0.45 (0.18; 1.13)	-0.82	0.48	0.44 (0.17; 1.13)
Evening (18-24)	1.05**	0.35	2.85 (1.43; 5.65)	1.08**	0.36	2.94 (1.46; 5.91)
Night (0-6)	1.70**	0.35	5.50 (2.75; 10.98)	1.74**	0.36	5.72 (2.83; 11.56)
Driver Age						
Less than 24	–	–	Reference	–	–	Reference
25 to 34 years	-0.07	0.31	0.93 (0.51; 1.71)	-0.07	0.31	0.93 (0.5; 1.72)
35 to 44 years	0.07	0.34	1.08 (0.55; 2.11)	0.06	0.35	1.06 (0.53; 2.11)
45 to 54 years	-0.02	0.41	0.98 (0.44; 2.18)	-0.07	0.42	0.94 (0.41; 2.14)
55 to 64 years	0.00	0.53	1.00 (0.36; 2.8)	-0.10	0.55	0.91 (0.31; 2.69)
65 years of over	2.21**	0.33	9.07 (4.8; 17.16)	2.24**	0.33	9.37 (4.91; 17.89)
Driver Condition						
Apparently Normal	–	–	Reference	–	–	Reference
DUI	2.16**	0.26	8.64 (5.21; 14.32)	2.18**	0.26	8.82 (5.29; 14.69)
Physical Impairment	4.03**	0.63	56.47 (16.56; 192.63)	4.00**	0.65	54.61 (15.14; 197)
Asleep/Fainted/Fatigued	-0.80	0.84	0.45 (0.09; 2.34)	-1.20	1.02	0.30 (0.04; 2.24)
Illness	1.46	0.87	4.30 (0.79; 23.44)	1.09	1.04	2.98 (0.39; 23)
Driver Residency Distance						
Less than 25 Miles	–	–	Reference	–	–	Reference
Greater than 25 Miles	-0.59*	0.24	0.55 (0.35; 0.88)	-0.61*	0.24	0.54 (0.34; 0.87)
Less than 5 years	–	–	Reference	–	–	Reference
5 to 15 years	0.38	0.27	1.47 (0.87; 2.46)	0.40	0.27	1.49 (0.88; 2.52)
More than 15 years	0.76*	0.35	2.15 (1.09; 4.23)	0.77*	0.35	2.15 (1.08; 4.29)
Vehicle Damage						
Minor/None Visible	–	–	Reference	–	–	Reference
Major Not Disabled	0.27	0.39	1.31 (0.54; 3.28)	0.26	0.40	1.30 (0.55; 3.33)
Major and Disabled	1.51*	0.37	4.53 (2.25; 9.08)	1.50*	0.38	4.49 (2.26; 9.15)
Vehicle Towed?						
No	–	–	Reference	–	–	Reference
Yes	0.96*	0.41	2.61 (1.17; 5.83)	0.95*	0.42	2.58 (1.14; 5.83)

CU Driver Airbag Status						
Not Deployed	–	–	Reference	–	–	Reference
Deployed	1.09**	0.25	2.99 (1.83; 4.87)	1.11**	0.25	3.04 (1.86; 4.97)
Roadway Condition						
Dry	–	–	Reference	–	–	Reference
Wet	-0.98**	0.35	0.37 (0.19; 0.75)	-1.04**	0.36	0.35 (0.18; 0.72)
Intercept	-8.68**	0.68	–	-8.93**	0.71	–
Number of Observations:	57,132			57,132		
LL at Convergence:	-472.983			-506.042		
Wald χ^2 (31)	336.700			367.980		
Prob> χ^2	0.000			0.000		
AIC	1,009.97			1,076.08		
BIC	1,296.47			1,362.58		
Notes: ** Significant at the 99% confidence interval * Significant at the 95% confidence interval						

Time Information

The variables in this group describe the temporal distribution of the Interstate crashes in terms of month, day, and hour. The analysis of the crashes showed statistically significant differences in terms of the month of the year between the two types of crashes. WWD crashes were observed to be more frequent in the months of March, May, and November, accounting for nearly half of all WWD crashes. Crashes that happened in March, May, and November are 3.19, 3.47, and 3.56 times more likely to be WWD, respectively. Even though the data analysis showed that WWD crashes were more likely during these three months, no specific reasons were found to explain this phenomenon. Further studies and more data are needed to determine whether the same trend persists over a longer time period.

Four periods (categories) were considered for the time of day mainly because of the lighting condition. The hourly distribution also varied throughout the hours of the day, with the late-night and early-morning times comprising the highest frequency of WWD crashes. More specifically, evening and night periods account for about 80% of the total WWD crashes. The results showed that crashes happened during the evening are 2.85 times more likely to be a result of WWD maneuvers. For the nighttime condition, this number increases to 5.50, implying the role of lighting condition and time of day in the probability of WWD crashes. This result is in line with some other studies (*3*, *8*, and *28*).

Responsible Driver

According to the estimation results presented in Table 4, driver age is found to significantly differentiate between WWD and non-WWD crashes on Interstates in Alabama. While statistically significantly different from other types of crashes, drivers older than 65 years are overrepresented when it comes to WWD. Specifically, drivers older than 65 are 9.07 times more probable to get involved in a WWD crash. This finding which is consistent with the studies by Braam (*4*) and Lathrop (*10*), is perhaps related to the diminished visual ability by aging that cause difficulties for this age group to see the signage and pavement markings, specifically during nighttime condition when lighting may be inadequate. The findings of a study by Gibbons (*29*) could recognize a relationship between aging and nighttime driving behaviors signifying

that older drivers have more difficulty detecting objects than younger drivers when the roadway is not lit and suggesting an interaction between these two variables.

The driver's physical/mental condition also delineates between WWD crashes and the other types of crashes since nearly half of the WW drivers were DUI, whereas less than 4% of drivers in non-WWD crashes were intoxicated. Being statistically significant, DUI drivers and physically impaired drivers are 8.64 and 56.47 times, respectively, more likely to experience WWD crashes on Alabama Interstates. Previous studies have found extensive correlation between alcohol consumption and impaired driving that causes difficulties for drivers in perceiving roadway information (*30* and *31*).

An interesting finding is that the majority of WW drivers had the crash within 25 miles of their residential location. From the corresponding OR presented in the Table 4, it can be inferred that drivers who had the crash at locations farther than 25 miles from their dwelling place are less probable (half of the other drivers) to get involved in WWD crashes, suggesting that distraction (due to factors like intoxication) might play a considerable role in these kinds of crashes. A detailed look at the data shows that nearly 60% of drivers with a residency place of less than 25 miles from their crash location were DUI while this number for drivers with the WWD crash happened farther than 25 miles from their residency location drops to 40%. These statistics may explain why close-to-home drivers are more likely to get involved in WWD crash.

Vehicle Information

When comparing WWD with non-WWD crashes, vehicle age was found to be a statistically significant factor. As shown in Table 3, WWD vehicles tend to be older compared to non-WWD vehicles. This difference is reflected in the results so that vehicles older than 15 years are more likely to be the causal unit of the WWD crash (2.15 times). Major and disabling damage to WWD vehicles is disproportionally high, with an OR of 4.53. This could be linked to the fact that the majority of WWD crashes are head-on or opposite-direction sideswipe crashes with more severe damage to the vehicles than other Interstate crash types, resulting in more vehicles being towed after WWD crashes (OR=2.61). Airbag deployment is also almost three times more probable (OR=2.99) in WWD crashes than in other types of crashes mainly due to the severe nature of the WWD crashes as well as frontal impact that typically occurs.

Environmental Condition

This group identifies the other environmental conditions for Interstate crashes. Based on the results, the type of setting (urban vs. rural) did not enter the final model to make a significant difference among different types of crashes on Interstates in Alabama, although this factor was found to be important by Zhou et al. (*8*). Roadway conditions were also found to characterize WWD crashes so that these kinds of crashes are more prevalent when the roadway surface is dry.

CONCLUSIONS AND RECOMMENDATIONS

This research aimed to identify and verify the true WWD crashes using five years of Alabama crash data (2009-2013). These verified WWD crashes were then combined with other non-WWD crashes within the same time period on Alabama Interstates to characterize WWD crashes. Given the rareness of the WWD events (around 0.16% of total Interstate crashes in our dataset), the Firth's penalized-likelihood logistic regression model was suggested. Using this method, the effect of all the confounding variables was examined and the corresponding OR to indicate the relative effect of the significant variables was calculated. The summary results of this model

(Table 4) clearly indicate a variety of factors that can characterize and affect the probability of WWD crashes on Interstates. The estimates of the binary model was also provided. Two information criteria (AIC and BIC) were calculated for both models. The comparison between these two values shows that given our dataset, the Firth's model outperforms the binary model. Lower standard error of parameter estimates for Firth's model also implies more accurate estimations.

According to results from the fitted model, drivers who cause WWD crashes are more likely to be 65 and older (OR=9.07), to be physically impaired (OR=56.47), to be under the influence of alcohol and drugs (OR=8.64), to drive during the evening (OR=2.85) or night (OR=5.50) when there will probably not be ample lighting, to reside in the vicinity of the crash scene (OR=Reference), and to drive vehicles older than 15 years (OR=2.15). Moreover, WWD crashes can be characterized by airbag deployment (OR=2.99), causing major and disabling damage to the primary vehicle (OR=4.53), being towed after the crash (OR=2.61), happening in March (OR=3.19), May (OR=3.47), and November (OR=3.56), and occurrence on dry roadways (OR=Reference).

Based on the empirical findings of the present study and, specifically, obtained ORs, several countermeasures and recommendations can be suggested to help mitigate the WWD issue on Alabama Interstate. These countermeasures can be grouped into three categories of education, engineering, and enforcement. Educational programs and behavior-based countermeasures should specially target older and DUI drivers given that these two driver groups were significantly overrepresented with higher ORs. Considering that drunk driving occurs most often during evening and night, it was expected that these two variables would both be significant. As for the driver age, the issue might be related to the diminished eyesight and contrast sensitivity of older drivers due to the aging process. Moreover, as drivers grow older, some other abilities such as attention and perceptual processes decrease and the possibility of experiencing impairment while driving increases (*32*), which in turn intensifies the possibility of WWD movements. One key point in educating older drivers is that this age group does not need more information about traffic rules, rather, they need to understand if they are able to safely drive (*33*). This has been the motivation for some states to provide a self-assessment tool for senior drivers and help them learn about their abilities to drive. Concerning the increasing percentage of older population in Alabama, this age group should be given special attention.

The finding also substantiates the significant role of DUI driving and necessitates the establishment of relevant prevention campaigns and the promotion of stricter rules. In 2014, Alabama joined other 20 states in the U.S. to legislate the use of ignition interlock devices (IIDs) for the first-time convicted drunk drivers. Having the 2014 WWD data can help evaluate the effectiveness of this newly acted law on the number of WWD crashes caused by intoxicated drivers. Studies have shown promising results with the use of IIDs in reducing the recidivism rate among alcohol impaired drivers (*34*–*36*). The present study identified the statically significantly increased probability of WWD crashes during evening (2.85 times) and night (5.50). Other than the prevalence of DUI drivers during these hours, the problem with lighting (*37*) as well as possible drowsiness and fatigue can worsen the situation.

Driver residency distance was found a contributing factor. The inclusion of this factor in the final model, meaning that WW drivers are more likely to be close-to-home drivers, suggests the role of distraction, whether as a result of intoxication or of aging, in the probability of WWD. Vehicle age was also the factor that was significant in the Firth's model. The importance of this parameter in the final model can define the economic status of the families based on social

processes, such as education. A study by Mohammadian and Miller (*38*) demonstrated that people with higher level of education are more likely to purchase new vehicles, which reflects their higher salaries compared to people with less formal education. Finally, WWD crashes could be distinguished by the roadway condition, the extent of damage to the vehicle, and the airbag deployment. The latter is related to the type of crash, which is severe and more likely to cause deployment of airbags.

Similar to most studies, this study also has some limitations. For example, the data used in this study is just from one U.S. state. Incorporating more data from other states not only bolsters the sample but also can lead to a more comprehensive result and help in developing nationwide countermeasures and strategies. Another limitation of this study comes from the inevitable role of human error in data collection process by police officers that affects the level of detail and accuracy for the obtained significant variables.

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REFERENCES

1. Pour-Rouholamin, M., H. Zhou, J. Shaw, and P. Tobias. Overview of Safety Countermeasures for Wrong-way Driving Crashes. *ITE Journal*, 2014, 84 (12), pp. 31-38.
2. National Highway Traffic Safety Administration, Fatality Analysis Reporting System (FARS) Encyclopedia, Washington, D.C., http://www-fars.nhtsa.dot.gov/main/index.aspx. Accessed February 10, 2015.
3. Cooner, S. A., and S. E. Ranft. Wrong-way Driving on Freeways: Problems, Issues and Countermeasures. *87th Annual Meeting of Transportation Research Board*, Washington, D.C., 2008.
4. Braam, A. C. Wrong-way Crashes: Statewide Study of Wrong-way Crashes on Freeways in North Carolina. North Carolina Department of Transportation, July 2006. https://connect.ncdot.gov/resources/safety/Documents/Crash%20Data%20and%20Information/WrongWayCrash.pdf. Accessed June 15, 2015.
5. Scaramuzza, G., and M. Cavegn. Wrong-way Drivers: Extent-interventions. The European Transport Conference, Leeuwenhorst Conference Centre, The Netherlands, 2007.
6. Zhou, H., J. Zhao, R. Fries, M. R. Gahrooei, L. Wang, B. Vaughn, K. Bahaaldin, and B. Ayyalasomayajula. *Investigation of Contributing Factors Regarding Wrong-way Driving on Freeways*. Publication FHWA-ICT-12-010. Illinois Center for Transportation, 2012.
7. Kemel, E. Wrong-way Driving Crashes on French Divided Roads. *Accident Analysis & Prevention*, 2015, 75, pp. 69-76.
8. Zhou, H., J. Zhao, M. Pour-Rouholamin, and P. Tobias. Statistical Characteristics of Wrong-Way Driving Crashes on Illinois Freeways. *Traffic Injury Prevention*, 2015, 16, pp. 760-767.
9. Zhou, H., and M. Pour-Rouholamin. *Guidelines for Reducing Wrong-Way Crashes on Freeways*. Publication FHWA-ICT-14-010. Illinois Center for Transportation, 2014.
10. Lathrop, S. L., T. B. Dick, and K. B. Nolte. Fatal Wrong-way Collisions on New Mexico's Interstate Highways 1990–2004. *Journal of Forensic Sciences*, 2010, 55 (2), pp. 432–437.
11. Xing, J. Characteristics of Wrong-way Driving on Motorways in Japan. *IET Intelligent Transport Systems*, 2015, 9(1), pp. 3-11.

12. Torrão, G., M. Coelho, and N. Rouphail. Modeling the Impact of Subject and Opponent Vehicles on Crash Severity in Two-Vehicle Collisions. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2432*, Transportation Research Board of the National Academies, Washington, D.C., 2014, pp. 53-64.
13. Perez-Fuster, P., M. F. Rodrigo, M. L. Ballestar, and J. Sanmartin. Modeling Offenses among Motorcyclists Involved in Crashes in Spain. *Accident Analysis & Prevention*, 2013, 56, pp. 95-102.
14. Haque, M. M., H. C. Chin, and H. Huang. Modeling Fault among Motorcyclists Involved in Crashes. *Accident Analysis & Prevention*, 2009, 41(2), pp. 327-335.
15. Larsen, K., R. Buliung, and G. Faulkner. Safety and School Travel: How Does the Environment Along the Route Relate to Safety and Mode Choice? In *Transportation Research Record: Journal of the Transportation Research Board, No. 2327*, Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 9-18.
16. Qin, X., K. Wang, and C. Cutler. Logistic Regression Models of the Safety of Large Trucks. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2392*, Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 1-10.
17. Sarkar, S., R. Tay, and J. Hunt. Logistic Regression Model of Risk of Fatality in Vehicle-pedestrian Crashes on National Highways in Bangladesh. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2264*, Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 128-137.
18. Xu, S. H. H. Wu, Q. S. Zhao, X. F. Shen, Z. R. Guo, and F. Z. Wang. The Median Effective Volume of Crystalloid in Preventing Hypotension in Patients Undergoing Cesarean Delivery with Spinal Anesthesia. *Revista Brasileira de Anestesiologia*, 2012, 62 (3), pp. 318-324.
19. Mulla, Z. D., A.A. Eziefule, and T. Carrillo. Preeclampsia in Early Adolescence: Dealing With Sparse Data, *Annals of Epidemiology*, 2012, 22(9), pp. 676-677.
20. Critical Analysis Reporting Environment. Alabama Traffic Crash Statistics. http://care.cs.ua.edu. Accessed February 10, 2015.
21. King, G., and L. Zeng. Logistic Regression in Rare Events Data. *Political Analysis*, 2001, 9.2, pp. 137-163.
22. Hosmer, D. W., Jr. S. Lemeshow, and R. X. Sturdivant. *Applied Logistic Regression, Third Edition*. John Wiley & Sons, Hoboken, New Jersey, 2013.
23. Gao, S., and J. Shen. Asymptotic Properties of A Double Penalized Maximum Likelihood Estimator in Logistic Regression. *Statistics & Probability Letters*, 2007, 77(9), pp. 925-930.
24. Firth, D. Bias Reduction of Maximum Likelihood Estimation. *Biometrika*, 1993, 80(1), pp. 27-38.
25. Heinze, G., and M. Schemper. A Solution to the Problem of Separation in Logistic Regression. *Statistics in Medicine*, 2002, 21, pp. 2409-2419.
26. Van der Paal, B. A Comparison of Different Methods for Modelling Rare Events Data. Ghent University, 2014.
27. Heinze, G., M. Ploner, and D. Dunkler. logistf: Firth's Bias Reduced Logistic Regression. R package version 1.21. *R Foundation for Statistical Computing*, Vienna, Austria, 2013.
28. Morena, D. A., and T. J. Leix. Where These Drivers Went Wrong. Public Roads, 2012, 75(6), pp. 33-41.
29. Gibbons, R. B., C. J. Edwards, R. Bhagavathula, P. Carlson, and D. A. Owens. Development of Visual Model for Exploring Relationship between Nighttime Driving Behavior and

Roadway Visibility Features. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2298*, Transportation Research Board of the National Academies, Washington, D.C., 2012, pp. 96-103.

30. Christoforou, Z., M. Karlaftis, and G. Yannis. Effects of Alcohol on Speeding and Road Positioning of Young Drivers: Driving Simulator Study. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2281*, Transportation Research Board of the National Academies, Washington, D.C., 2012, pp. 32-42.
31. Kuypers, K. P. C., N. Samyn, and J.G. Ramaekers. MDMA and Alcohol Effects, Combined and Alone, on Objective and Subjective Measures of Actual Driving Performance and Psychomotor Function. *Psychopharmacology*, 2006, 187(4), pp. 467–475.
32. Glisky E. L. Changes in Cognitive Function in Human Aging. *Brain Aging: Models, Methods, and Mechanisms*. CRC Press, Boca Raton, FL, 2007.
33. Keskinen, E. Education for Older Drivers in the Future. *IATSS Research*, 2014, 38(1), pp. 14-21.
34. Pour-Rouholamin, M., and H. Zhou. Current Practices of Safety Countermeasures for Wrong-Way Driving Crashes. *94th Annual Meeting of Transportation Research Board*, Washington, D.C., 2015.
35. Raub, R. A., R. E. Lucke, and R. I. Wark. Breath Alcohol Ignition Interlock Devices: Controlling the Recidivist. *Traffic Injury Prevention*, 2003, 4(2), pp. 98–104.
36. Rauch, W. J., E. M. Ahlin, P. L. Zador, J. M. Howard, and G. D. Duncan. Effects of Administrative Ignition Interlock License Restrictions on Drivers with Multiple Alcohol Offenses. *Journal of Experimental Criminology*, 2011, 7, pp. 127–148.
37. Pour-Rouholamin, M., and H. Zhou. Mitigating Wrong-Way Movements near Interchange Areas Using Access Management Techniques. *94th Annual Meeting of Transportation Research Board*, Washington, D.C., 2015.
38. Mohammadian, A., and E. Miller. Empirical Investigation of Household Vehicle Type Choice Decisions. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1854*, Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 99-106.