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ITS Impacts on Safety and Traffic Management: An Investigation of Secondary Crash Causes

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Freeway service patrols, an increasingly popular choice in combating the effects of traffic incidents on freeway operations, have been known to reduce incident response and clearance time. This reduction can help alleviate the delay due to non-recurrent, incident related congestion, as well as lower the chance of secondary crashes. While much work has been done in the direction of identifying the benefits stemming from the delay savings by freeway patrols, little has been done to identify the potential savings from lowering the likelihood of secondary crash occurrence. Using a 5-year incident data base from the Borman Expressway, we develop logistic regression models to examine what primary crash characteristics are likely to influence the likelihood of a secondary crash. The findings suggest that clearance time, season, type of vehicle involved, and lateral location of the primary crash significantly influence the likelihood of secondary crash occurrence. Further, the 1995 potential benefit from secondary crash reduction was $568,080 exceeding the 1995 Hoosier Helper freeway service patrol program costs by a factor of 1.38. Given a better understanding of what contributes to secondary crash occurrence, various components of incident management can be operated at a higher level of cost-effectiveness.

Keywords: Incident management; Safety analysis; Secondary incidents; Crashes

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INTRODUCTION

In search for an approach to combat the effect of traffic incidents on freeway operation, several states have made freeway service patrols an increasingly popular choice in larger urban areas. It is believed that an efficient deployment of freeway service patrol vehicles substantially reduces incident response and clearance times which, in turn, alleviate the delay attributed to non-recurrent, incident related congestion and lower the chance of secondary crashes. Previous studies have estimated an 8 min duration reduction of a stall in Minneapolis and a 16.5 min average duration reduction of an incident in Houston as a result of freeway service patrol operation (MnDOT, 1994; Hawkins, 1993). Morris and Lee (1994) have summarized the results of six freeway service patrol evaluation studies which yielded benefit–cost ratios ranging from 2:1 to 36:1, but the benefits only account for delay savings by a freeway service patrol. Secondary crash reduction may represent another significant benefit of freeway service patrols. These programs reduce total primary incident duration, which is a possible contributor to secondary incidence occurrence. Research by Raub (1997) concluded that more than 15% of all crashes in their study may have been caused by an earlier incident. However, one question remains: what primary crash characteristics are likely to influence the chance of a secondary crash? Very little or no information is available in the literature on the relationship between the characteristics of primary incidents and the occurrence of secondary crashes. The absence of such research can be attributed, in part, to the high cost of collecting crash data, largely due to the extensive field surveillance required.

This paper employs a logistic regression approach to incident data provided by Indiana's Hoosier Helper freeway service patrol program. Specifically, a logistic regression model will be fit to crash data to determine the effects of several primary crash descriptors (clearance time, season, weekday vs. weekend, type of vehicle involved, lateral location, etc.) on the probability of secondary crash occurrence. The model results can be useful in estimating the extent to which Hoosier Helper improves road safety by reducing secondary crash likelihood. In addition, a better understanding of what contributes to secondary crash occurrence can be achieved. As a result, operators can adjust Hoosier Helper patrol strategies to further reduce those secondary crashes. For example, additional patrol vehicles may be deployed and/or motorist assist procedures altered during times of high secondary crash likelihood. Further, prioritization procedures can be instituted which will provide assistance to the types of accidents that have the highest likelihood of being followed by a secondary crash. The results of this study can, in general, improve the cost-effectiveness of various Intelligent Transportation Systems (ITS) technologies (e.g. machine vision and closed circuit television) for incident management because operators can initiate appropriate and effective responses, given real-time information, concerning crash characteristics. This methodology can be applied to any similar set of incident data.

BACKGROUND INFORMATION

The Hoosier Helper program in Northwest Indiana is a service patrol program initiated in September 1991. The program, supported by the Indiana Department of Transportation (IN-DOT), maintains a fleet of six vehicles. Hoosier Helper crews patrol a 16-mile stretch of Interstate 80–94 near Gary, commonly known as the Borman Expressway, and an 8-mile portion of Interstate 65, looking for and responding to incidents. Examples of motorist assists include providing support at crash sites, supplying fuel, changing flat tires, and calling tow truck operators. Hoosier Helper patrolmen maintain a daily activity log which documents all assists made. After completing an assist, a patrolman will record the following information regarding the incident: time of arrival, road, direction, mile marker, state and license plate number of vehicle assisted, type of vehicle assisted, lateral location of incident, services rendered, and departure time. IN-DOT compiles the daily activity logs continuously and appends them to the Hoosier Helper assist database, which contains records of incidents since the start of the program. The database provides the incident data used in this study.

DATA ANALYSIS

Secondary Crash Determination

A primary crash is said to cause a secondary crash if the two incidents meet a set of assumed spatial and temporal criteria. A straightforward

TABLE I Vehicle type and traffic volume distribution by lane for the Borman Expressway (average of 5 weekdays and 4 weekend days in March 1992)

Lateral location	*Percent cars and vans*	*Percent trucks*	*Percent semis*	*Percent volume served*
Left lane (weekday)	54.0	15.0	26.9	31.3
Center lane (weekday)	47.3	8.6	38.6	39.7
Right lane (weekday)	92.3	5.5	1.0	29.0
Total (weekday)	62.4	9.7	24.0	
Left lane (weekend)	68.6	12.4	14.8	30.9
Center lane (weekend)	70.7	6.2	17.1	39.9
Right lane (weekend)	93.2	5.2	0.2	29.2
Total (weekend)	76.6	7.8	11.5	

method, proposed by Raub (1997), was used to establish the parameters linking the two events. Using the available data from 1992 through 1995, a crash was labeled secondary if it occurred no more than 0.8 km (later increased to 1.5 km) upstream and during the clearance period plus 15 min of the primary crash (Raub, 1997). Using these criteria, 35% of all crashes in our study, during the specified four year period, could be attributed to a primary crash and were thus classified as secondary crashes.

This distance is considered realistic for the Borman Expressway, where average daily traffic counts register approximately 140,000 vehicles per day. Table I contains expanded information regarding traffic operations on the Borman Expressway. Raub (1997) suggested that if high (near capacity) traffic flow approaches an incident, then the resulting queue can grow at a rate of about 8.5 miles per hour.

Primary Crash Characteristics

Tables II–V present a distribution of primary crashes by vehicle type, season, weekday/weekend, and lateral location respectively. The tables provide primary crash counts disaggregated by secondary crash association. A code of 0 refers to a primary crash *not* followed by a secondary crash. Conversely, a code of 1 represents a primary crash followed by a secondary crash, given the previously stated assumptions. The study considered 741 primary crashes, 484 of which were classified as code 0 primary crashes, and 257 as code 1.[1]

[1]A more elaborate analysis, including other types of incidents besides crashes, was attempted. Unfortunately the database available cannot fully support such an analysis.

TABLE II Borman Expressway primary crashes by vehicle type

Crash code	*Vehicle type*				*Total*
	Car	*Van*	*Truck*	*Semi*	
0	330	26	43	74	473
1	191	2	15	43	251

TABLE III Borman Expressway primary crashes by season

Crash code	*Season*				*Total*
	Fall	*Winter*	*Spring*	*Summer*	
0	136	142	116	90	484
1	74	59	63	61	257

TABLE IV Borman Expressway primary crashes by weekday/weekend

Crash code	*Weekday*	*Weekend*	*Total*
0	348	136	484
1	200	57	257

TABLE V Borman Expressway primary crashes by lateral location

Crash code	*Lateral location*								*Total*
	Median shoulder	*Right shoulder*	*Left lane*	*Center lane*	*Right lane*	*Ramp*	*Total shoulder*	*Total in-lane*	
0	74	237	47	33	43	34	311	123	468
1	30	123	31	23	27	15	153	81	249

An analysis of primary crashes within the study period found that a great majority involved cars. A further investigation into the occurrence of secondary crashes revealed 37% of car and semi (trucks with more than four axles) primary crashes were associated with a secondary crash.[2] The lowest number of primary crashes happened in the summer; however, that period marked the largest percentage of code 1 (primary crash associated with a secondary crash) primary crashes, with 40%. With regard to weekday primary crashes, 36%

[2] In this paper, we refer to single unit trucks as trucks and combination trucks as semis.

TABLE VI Borman Expressway primary crash clearance times

Category	Crash code					
	0		1		Overall	
	Mean	*STD*	*Mean*	*STD*	*Mean*	*STD*
Fall	23.15	18.52	38.23	28.90	28.46	23.78
Winter	24.80	19.68	34.81	27.95	27.74	22.82
Spring	19.93	15.09	29.06	16.50	23.15	16.15
Summer	22.40	17.91	33.13	20.77	26.74	19.77
Weekday	23.00	18.37	33.87	22.94	26.97	20.80
Weekend	22.01	17.23	34.40	29.06	25.67	22.07
Car	22.69	17.68	32.66	21.85	26.35	19.88
Van	18.12	16.03	22.00	11.31	18.39	15.61
Truck	19.58	14.78	34.93	23.05	23.55	18.37
Semi	26.82	21.63	39.53	34.85	31.50	27.79
Median shoulder	21.42	15.17	31.10	20.28	24.21	17.39
Right shoulder	20.78	17.38	29.76	21.53	23.84	19.35
Left lane	23.94	17.72	30.16	15.86	26.41	17.17
Center lane	26.36	22.78	42.96	21.98	33.18	23.73
Right lane	27.00	19.54	46.89	39.65	34.67	30.33
Ramp	26.88	18.32	37.53	19.24	30.14	19.06
Total shoulder	20.93	16.86	30.02	21.30	23.93	18.91
Total In-lane	25.66	19.69	39.37	28.18	31.10	24.31
Overall	22.72	18.04	33.99	24.37	27.00	21.00

were connected to secondary crashes. Further, 40% of primary crashes occurring in a lane were linked to secondary crashes.

Table VI contains primary crash clearance time statistics for all categories considered in the previous four tables. The difference between the mean of a code 0 and a code 1 primary crash range between 3.88 and 19.89 min for each classification. In fact, the variation between the two average clearance times exceeded 10 min in nine of the 16 individual categories, and an overall comparison of code 0 and code 1 primary crash means yielded an 11.27 min difference. The logistic regression analysis will attempt to determine whether clearance time and a host of other primary crash characteristics have an impact on the likelihood of secondary crash occurrence.

MODEL DEVELOPMENT AND ESTIMATION

The Logistic Regression Model

Regression based methods represent an integral part of any data analysis concerned with describing a response (dependent) variable as a function of one or more explanatory variables. The response variable merits special attention when determining the appropriate regression method. In the usual multiple regression framework the dependent variable is assumed to be continuous. This framework is not appropriate when the dependent variable is discrete; rather, qualitative response (QR) models should be used. In this study the dependent variable is binary (0/1), since it takes the value of 0 for primary crashes not linked to secondary crashes, and 1 for primary crashes linked to secondary crashes. QR models recognize the discrete nature of this dependent variable and yield predictions that take one of these two values depending on a vector of exogenous variables.

Much along the lines of multiple regression, this paper is interested in specifying a relationship between the probability of a secondary crash following a primary crash based on a set of characteristics (independent variables). While we can expect a direct relationship between the characteristics and the dependent variable, a more plausible objective, in the case of QR models, is to predict the *likelihood* that a secondary crash occurs given the characteristics of the primary crash (Pindyck and Rubinfeld, 1991). To depict this relationship, we use the familiar logistic regression formulation:

$$\log\left(\frac{P_i}{1 - P_i}\right) = \alpha + \boldsymbol{b}'\boldsymbol{x}_i, \tag{1}$$

where $\boldsymbol{b}$ is the vector of parameters to be estimated and $\boldsymbol{x}_i$ the vector of exogenous variables for primary crash i. In this form of the logistic regression model, the dependent variable is the logarithm of the odds that a particular choice (0/1) will be made. Therefore, the logistic model transforms the problem of predicting probabilities within a (0,1) range to a problem of predicting the odds of a secondary crash occurring.

The Independent Variables

In order to establish a link between the clearance time of a primary crash and the likelihood of secondary crash occurrence, a series of explanatory variables were considered for possible inclusion into the logistic regression model. The variables depict primary crash characteristics. In essence, the study seeks to determine *what characteristics* *of the primary crash increase the likelihood of secondary crash occurrence*. A strong possibility exists that the following primary crash characteristics can influence the likelihood of secondary crash occurrence:

- *Clearance time* (*CLT*): It is generally assumed that the likelihood of a secondary crash caused by a driver upstream of a primary crash increases as primary crash clearance time increases (the longer a disabled vehicle remains on the roadway, the higher the likelihood that a secondary crash will occur).
- *Vehicle type*: The vehicle type may influence the clearance time of the primary crash; larger vehicles (e.g. single unit and semi trucks) require a longer clearance time. This variable may also influence a driver's ability to detect a crash downstream, thus placing the driver at risk because of inadequate sight distance or impatient behavior resulting from congestion delays (vehicles considered were cars (CAR), trucks (TRK), semis (SEMI), vans (VAN), and buses (BUS)).
- *Vehicle location:* This stands as an indirect measure (proxy) of the prevailing speed of traffic (vehicles move faster on the left and center lanes as opposed to the ramp and the right lane). Further, operating speed influences stop times for avoiding involvement in a secondary crash (locations considered: left lane (LL), right lane (RL), center lane (CL), median shoulder (MS), right shoulder (RS), and ramp (RMP)).
- *Season:* It has been established that the prevailing weather conditions affect the driving conditions (traction and visibility) which, in turn, may influence the behavior of motorists and the likelihood of secondary crash occurrence (seasons: winter (WNT), spring (SPR), summer (SMR), and fall (FL)).
- *Day of the week:* This measure acts as a proxy for the traffic volumes, vehicle mix, and possibly driver attitudes and familiarity (days: weekdays (WKD), and weekends (WND)).

Model Estimation

Starting with the initial set of 18 explanatory variables, the next step was to select the variables that "best" capture the likelihood of a

TABLE VII Estimation results for logistic regression models

Variable name	*Model 1*			*Model 2*		
	Coefficient estimate	*t-Ratio*	*Odds ratio*	*Coefficient estimate*	*t-Ratio*	*Odds ratio*
Constant	−2.32	5.3			−2.44	5.61
Clearance time	0.027	6.72	1.028			
Clearance time (specific to winter)	—	—	—	0.017	3.26	1.018
Clearance time (specific to spring, summer, fall)	—	—	—	0.031	6.69	1.032
Car	0.966	2.36	2.62	0.964	2.34	2.62
Truck	0.442	0.76	1.55	0.415	0.67	1.51
Semi	0.762	1.71	2.14	0.731	1.67	2.07
Winter	−0.402	2.11	0.66	—	—	—
Weekday	0.346	1.81	1.41	0.353	1.83	1.42
Ramp/median	−0.264	1.32	0.76	−0.248	1.21	0.78
Summary Statistics						
Number of observations	741			741		
$L(0)$	956.57			956.57		
$L(B)$	580.34			558.22		
ρ^2	0.39			0.41		

primary crash being followed by a secondary crash. In developing the models, we used a series of rigorous likelihood ratio tests (LRT), as well as Akaike's Information Criterion (AIC) (Greene, 1993).[3]

The estimation results are shown in Table VII. The coefficients for the variables are mostly as expected: increased clearance time for the primary crash leads to higher likelihood of secondary crash occurrence, similar to most hypotheses in the literature (Judycki and Robinson, 1992; Korpal, 1992). It should be noted that we developed two different models. Model 1 includes clearance time as a single independent variable. Model 2 includes clearance time specific to winter and to all other seasons combined.[4] The coefficients for clearance time of Model 2 seem to suggest that an increase in primary crash clearance time increases the likelihood of a secondary crash in winter less than it does in other seasons. This might seem counter-intuitive at first, but it seems reasonable to expect that drivers are

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[3]AIC criterion was used to compare models. It is generally suggested that a model with a lower AIC value is "better" than a model with a higher AIC value.

[4]To develop Model 2, we initially developed a model where clearance time was specific to each season. Then, with a series of LRT tests, we could not reject the null hypothesis of equality of the coefficients of the clearance times specific to all seasons except winter.

inherently more careful over winter and drive at lower speeds, thus reducing the probability of a secondary crash (Brown and Baass, 1997).

All other coefficients are similar between the two models, both in terms of sign and magnitude. Our models suggest that primary crashes involving cars and semis have an increased likelihood of being associated with a secondary crash.[5] Crashes during weekdays also have a higher likelihood of being followed by a secondary crash, probably due to the higher traffic volumes during the weekdays. Further, it appears from our model that crashes occurring on ramps and medians have a lower probability of being associated with a secondary crash. Finally, the one additional coefficient of Model 1 (winter) suggests that primary crashes that occur during the winter have a lower likelihood of being followed by a secondary crash.

For this type of non-linear models, the measure of goodness-of-fit most commonly employed is ρ^2. Although this is a more informal goodness-of-fit index, it is analogous to the R^2 from regression. It is defined as $1-(L(\beta)/L(0))$, and measures the fraction of the initial log likelihood value explained by the model. The value of ρ^2 obtained from these models can be characterized as good for both Models 1 and 2 ($\rho^2 = 0.39, 0.41$, respectively) (Ben-Akiva and Lerman, 1985).

The results presented thus far can be useful in investigating the direction of effect of those factors that contribute to secondary crash occurrence, but we also wish to examine the magnitude of these effects. After fitting the model, the emphasis shifts from the computation and assessment of the significance of the estimated coefficients to interpretation of their values. The interpretation of a fitted model allows for practical inferences to be drawn from the estimated model coefficients. The interpretation involves determining the functional relationship between the dependent variable and the independent variable and defining the unit of change for the independent variable. The odds ratio (presented in Table VII for each coefficient of each model) is used to measure the strength of an association (Greene,

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[5]As it appears from the results, cars are more highly associated with secondary crash occurrence. Trucks (and semis-trucks in particular) have higher CLTs which could have suggested higher association to secondary crash occurrence than cars. Nevertheless, for other reasons (season, lateral location, etc.), despite the higher CLT of semis, cars are more highly associated with secondary crash occurrence.

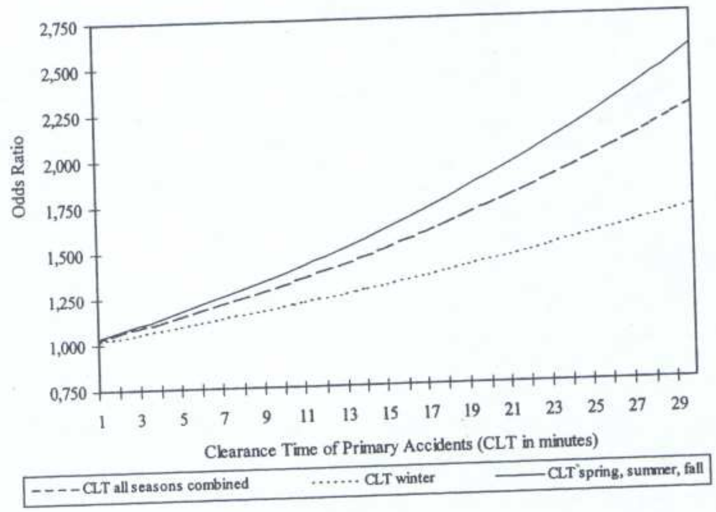

FIGURE 1 Probability of a primary crash being followed by a secondary crash.

1993). The odds ratio (OR) ranges from 0 to ∞. When OR is greater than 1, then the Code 1 crashes are more likely than the Code 0 crashes; when OR is less than 1, then the Code 0 crashes are more likely than the Code 1 crashes. For example, in Table VII the odds ratio of CLT from Model 1 is 1.028. This simply suggests that each minute increase in clearance time increases the likelihood of a Code 1 crash by 1.028, or 2.8%. Figure 1 shows that the probability of a primary crash being followed by a secondary crash increases with CLT and is lower at all times for accidents occurring during winter.

ESTIMATION OF SECONDARY CRASH REDUCTION BENEFITS

The odds ratios in Table VII serve to quantify the effect of primary crash descriptors on the probability of secondary crash occurrence. According to estimates by Sullivan (1996), freeway service patrols reduce crash duration via faster incident detection and response by an average of 10 min. Therefore, based on the results of Model 2, the likelihood of a secondary crash decreases by a factor of 1.185 ($e^{10*0.017}$) in winter and 1.363 ($e^{10*0.031}$) in all other seasons for

TABLE VIII Estimation of secondary crash reduction benefit

Season	*1995 HH crash assists*	*Potential sec. crashes reduced*	*Cost of crash per vehicle (1995 $)*	*Ave. number of vehicles in crash*	*Benefit (1995 $)*
Winter	110	25	1,482	1.48	54,834
Spring, Summer, Fall	411	234	1,482	1.48	513,246
Total	521	259			568,080

a 10 min decrease in primary crash clearance time. In other words, Hoosier Helper may help reduce secondary crash likelihood by 18.5% in winter and 36.3% in all other seasons per crash assisted.

The Hoosier Helper secondary crash reduction benefit may consist of two components: crash-related delay savings and crash cost savings. Table VIII presents the benefit produced through secondary crash reduction. Hoosier Helper completed 521 crash assists in 1995. Given the previously discussed reductions in secondary crash probability per primary crash assisted, the program may have eliminated as many as 259 potential secondary crashes. A study of crashes within the Hoosier Helper assist database revealed that each crash included an average of 1.48 vehicles; therefore, approximately 383 vehicles avoided involvement in and, at minimum, vehicle damage from a secondary crash. The National Highway Traffic Safety Administration (1996) reported an average cost per vehicle per crash of $1,445. This cost is made up of vehicle damages ($1,320) and additional travel delay ($125) resulting from a property damage only (PDO) crash. This 1994 figure was adjusted to 1995 dollars, $1,482, using the appropriate Consumer Price Indexes for the two PDO crash cost components (US Bureau of Census, 1996). The PDO crash cost would increase if the study accounted for other NHTSA stated PDO crash costs, including insurance administration costs, household productivity losses, workplace losses, and emergency service costs. The total potential 1995 benefit for secondary crash reduction was $568,080. In fact, this value exceeded the 1995 Hoosier Helper program costs of $411,231 by a factor of 1.38, thus justifying the statement that secondary crash reduction marks a significant benefit of freeway service patrols.

CONCLUSIONS

The goal of this study was to identify and quantify the effect of primary crash descriptors on the likelihood of secondary crash occurrence. Through a logistic regression analysis of incident data provided by Indiana's Hoosier Helper freeway service patrol program, the study yielded two logistic models representing those primary crash characteristics found to affect the likelihood of secondary crash occurrence on the Borman Expressway. These models contain four statistically significant primary crash descriptors found to increase the likelihood of secondary crash occurrence (CLT, CAR, SEMI, WKD), and two statistically significant descriptors which decrease the chance of a secondary crash (WNT, RMPMS). Odds ratios accompany each of the models' explanatory variables, allowing for practical inferences to be drawn from the estimated models. The results suggest that the Hoosier Helper program may reduce secondary crash likelihood by 18.5% in winter and 36.3% in all other seasons per crash assisted, because of an assumed average 10 min decrease in primary crash clearance time. As a result, the 1995 potential benefit for secondary crash reduction was $568,080, exceeding the 1995 Hoosier Helper program costs by a factor of 1.38. This model can be easily used both for explanatory and predictive purposes.

Given a better understanding of what contributes to secondary crash occurrence provided by the two logistic models in this paper, various components for incident management on the Borman Expressway can be operated at a higher level of cost-effectiveness. For example, operators may wish to consider adding a tow truck to the Hoosier Helper pick-up truck and van fleet for faster removal of disabled vehicles. The program will soon have an Expert System in place which allows a crew member to create and send highway advisory radio messages and variable message sign messages from the incident site, using an in-vehicle computer and transmitter. Keeping drivers upstream of a primary crash informed should reduce the likelihood of secondary crashes because of changes in driver attitude and the opportunity for motorists to divert around a primary crash.

While some ITS components for incident management focus on reducing the probability of a secondary crash, others seek to minimize secondary crash detection time. For instance, incident management personnel can use closed circuit television to monitor traffic upstream of a primary crash with characteristics that increase the chance of a secondary crash occurring. This example demonstrates how the methodology presented in this paper can improve road safety and the cost-effectiveness of various ITS technologies for incident management.

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