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What is the Role of Multiple Secondary Incidents in Traffic Operations?

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Abstract: Traffic incidents are a major source of uncertainty. Sometimes, a primary incident can result in multiple secondary incidents, which can be particularly problematic. To identify roadways where multiple secondary incidents are more likely to occur and analyze primary and secondary incidents, an innovative analysis method based on a detailed incident dataset from Hampton Roads was developed. Incidents occurring on major freeways are categorized as 1) independent, 2) one primary-secondary pair, and 3) one primary with two or more secondary incidents, including secondary incidents in the same and opposite directions. The last category captures large-scale events involving several secondary incidents. Ordinal regression models are estimated to quantify associations with key factors that include incident characteristics, roadway geometry and traffic flows. Furthermore, a deeper analysis of secondary incidents is conducted by examining the time gap between primary and secondary incidents. The time-gap is treated as conditional on the occurrence of secondary incidents and the appropriate statistical method, the Heckman model, is used for estimation. This research contributes to incident management by characterizing and analyzing complex events involving multiple secondary incidents. The results support the planning and operation of service patrols.

Keywords: Incident, Secondary Incident, Ordered Logit, Heckman Model, Hampton Roads.

INTRODUCTION

Traffic incidents, defined as non-recurring events that cause a reduction of roadway capacity, induce 30% to 50% of the congestion in urban areas *(1, 2, 3)*. Incidents include traffic crashes, disabled or abandoned vehicles, or road debris. Many traffic incidents do not cause congestion, while others can result in long delays and queues. Large-scale incidents can have a regional impact on traffic operations and cause major disruptions, e.g., incidents like a crashed tractor trailer which spills cargo, a vehicle rollover in a tunnel, vehicle fires, and crashes involving several vehicles, major damage, deaths, and injuries. Such incidents typically block or close transportation facilities for extended durations. From an incident management perspective, such incidents can result in secondary incidents, e.g., crashes as vehicles queue up, compounding the problem. While many studies have analyzed incident characteristics, knowledge about the role of secondary incidents especially multiple secondary incidents is limited. It is important to understand the role of such secondary incidents vis-à-vis other incidents. This study explores primary incidents that have multiple secondary incidents associated with them. To do this, secondary event adversity is defined as the number of secondary incidents in the same and opposite directions that are associated with a primary incident (note that in this paper we use the term event as a collection of one or more incidents). Different categories for secondary events are established according to their scale and traffic/safety impacts. This requires the development of a comprehensive identification method for secondary incidents. After analyzing the identified incidents, a set of research questions are answered:

- What are the problematic routes from the perspective of secondary event adversity?
- What factors are associated with secondary event adversity?
- What are the distributions and key effects of the time gaps between primary and secondary incidents?
- What are the implications for incident management?

A key objective of this study is to explore multiple secondary incidents from the perspective of incident management.

LITERATURE REVIEW

The authors could not find literature that addresses multiple secondary incidents, but there is extant literature on incidents and their management. Traffic incidents can induce delays and create unsafe driving situations. Some incidents can result in secondary incidents. If an incident causes (in part) another incident, the first incident is termed as the primary incident and the following incident is a secondary incident. However, it is difficult to retrieve this relationship from archived incident data. Previous researches have made a basic assumption that an incident can be defined as a secondary incident/crash if it happens within a certain upstream range and temporal period after a prior incident. The spatial and temporal boundary criteria must be determined for identification. Fixed spatial and temporal boundary criteria were used in secondary crash/incident identification by several researchers *(4,5,6)*. Raub and Karlaftis found that 15% of all crashes were secondary by using clearance time plus 15-minute period and one mile distance. However, Moore et al. *(6)* obtained the secondary proportion of about 1.5% to 3% by using even larger boundary conditions, two hour and two miles. This difference might be partly due to lack of data on crash duration, or inaccurate spatial and temporal boundaries. It may also reflect the different traffic and safety situations in the different areas.

Some previous studies have attempted to investigate major factors contributing to secondary incident occurrence. Karlafits et al. *(5)* applied a logistic regression model to examine what primary incident characteristics influence the likelihood of a secondary crash. They suggested that the clearance time, season, type of vehicle involved and lateral location of the primary crash are significant factors. Hirunyanitiwattana and Mattingly *(7)* have investigated differences between primary and secondary crash characteristics. They have found that the typical secondary crash is a rear-end, property damage only crash on a greater than 4-lane urban freeway. Secondary crashes were more likely to occur during the peak period and were often associated with speeding. Zhan et al. *(8)* identified five major factors influencing secondary incidents, which include the number of involved vehicles, the number of lanes, the duration of primary incident, the time of day, and the primary vehicle rollover.

An issue that is only partially covered in the literature is that of missed counting of associated incidents when fixed spatial and temporal thresholds are used. In Virginia, an incident is archived according to road segment code instead of its physical location, which is less than ideal for secondary incident identification. To identify secondary incidents, a segment-based identification method was developed in this study. It is similar to the methods used in previous research. The only difference is that instead of using a fixed length, the segment-based method uses non-overlapping segment length (i.e. within a segment) as a spatial boundary. Two possible limitations for the segment-based method and the previous research methods with a fixed spatial boundary are:

Missed counting situation (Figure 1-a). Crash C2 in Segment 2 is associated with Crash C1 in Segment 3. They are a pair of primary (C1) and secondary (C2) incidents. Because C2 is beyond the spatial boundary of the prior incident C1, this primary and secondary pair cannot be captured in the segment-based method or any fixed spatial boundary methods.

Over counting situation (Figure 1-b). The crash C3 and C4 in Segment 2, are associated with crash C1 in Segment 3. In reality, the primary is C1, the secondary incidents are C2, C3, and C4 (only C1 is their primary incident) but the segment-based identification shows two primary and secondary pairs [(C1, C2) and (C3, C4)]. More importantly, over counting will under-estimate the magnitude of primary and secondary incidents and therefore fall short in capturing this kind of a multiple incidents event.

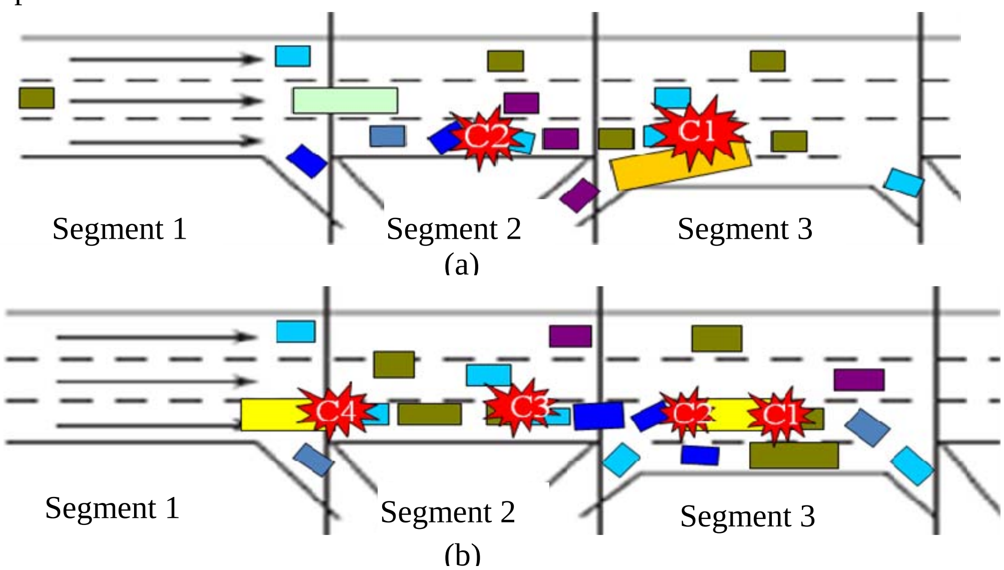

Figure 1: Missed Counting (a) and Over Counting (b) Scenario in the Secondary Incidents Identification

These two limitations can be overcome if the actual queue length of primary incidents is determined. Most of the studies on secondary incidents used queuing theory to analyze incident delay but only a few attempted to use dynamic boundary to improve the identification method. Sun *(9)* proposed an improved dynamic threshold methodology to extract secondary accidents. The analysis demonstrated that the static and dynamic methods can differ by over 30%. Similar problems also exist in a fixed temporal boundary—although they can be overcome by recording incident durations.

Despite developments in recent studies, several important issues have been neglected in the past. First, previous studies only use binary categories (i.e. an incident with or without secondary incidents) to estimate the likelihood of secondary incidents. This lacks a detailed secondary incident scale which accounts for multiple secondary incidents. For example, a primary incident with one secondary incident usually has less impact on traffic than a primary with two or more secondary incidents. Furthermore, secondary incidents in the opposite direction have not been considered in most previous studies. Clearly, a primary incident in one direction can contribute to not only secondary incidents in the same direction but also secondary incidents in the opposite direction. Teng et al. *(10)* have found that about 10% of accidents were associated with "rubbernecking" incidents in the opposite direction. This significant number suggests that secondary incidents in opposite direction should be taken into account. Finally, relatively little research has been done in analyzing the characteristics of secondary incidents. Most studies only focused on applying statistical models to analyze primary incidents and investigated the associated major factors likely leading to secondary incidents. However, critical questions relating to secondary incident itself remain unanswered. For instance, how soon will a secondary incident happen after a primary incident occurred? What is the distribution of time-gaps for different secondary incidents? What factors are associated with actual time difference between secondary incidents and their primary incident (time-gap)?

METHODOLOGY

The conceptual design for this research is shown in the following flow chart. First we obtained incident, traffic and road inventory data for the Hampton Roads area. The area includes cities like Virginia Beach, Norfolk, and Newport News, and it has a population of approximately 1.6 million, the 33rd-largest metropolitan area in the United States. Furthermore, the Hampton Roads Bridge-Tunnel (HRBT) and the Monitor-Merrimac Memorial Bridge-Tunnel (MMBT) are major crossings, and also sources of major traffic congestion. The Hampton Roads Beltway links seven of the largest cities in Hampton Roads and experiences flows of 100,000 to 150,000 vehicles per day. The area experiences major traffic congestion during peak hours and also due to incidents.

After defining categories for the secondary events, a comprehensive identification method for secondary events was developed by integrating incident data with traffic and road inventory data. This method is capable of capturing multiple secondary incidents over segments.

Objective: Identify, categorize and analyze secondary events

⇩

Obtain Data: 1. Incident data 2. Road inventory data 3. Traffic data

⇩

Conduct Analysis:

1. Define the categories for secondary events
2. Identify and classify secondary incidents in the same and opposite directions.
3. Estimate ordinal models to analyze secondary events severity
4. Apply distribution fitting for the time to secondary events
5. Use Heckman model to estimate the time to secondary incidents

⇩

Draw Conclusions:

1. What factors are associated with secondary event severity?
2. What factors are associated with time to secondary incidents?
3. What are implications for service patrols?

Figure 2: Research Design

Based on identified results, two generalized logit models *(11, 12)* on primary and non-primary (independent) incidents were used to estimate the major effects associated with secondary incidents. To understand the characteristics of secondary incidents, two important analyses were undertaken. The first was to calculate time-gap between identified primary and secondary incidents, and to perform a curve fitting in order to examine the time-gap distribution. The second is to identify the key factors associated with time-gaps based on Heckman model *(13)*. All results were analyzed to find implications for incident management.

Data Acquisition

Year 2005 incident data was obtained from the Traffic Operations Center in Hampton Roads. It contained vehicular based incident records including a total of 43 variables, such as incident ID, date, start time, incident duration, lane-effected, route name, direction, segment ID, *etc*. The road inventory data was contained in a GIS network and the traffic data used is Year 2005 AADT, both obtained from the Virginia Department of Transportation (VDOT).

Secondary Events Definition and Classification

Secondary events are defined in Table 1. The table shows three categories: any independent incident, i.e., a single incident without secondary events, and a collection of primary incidents with associated same direction and opposite direction secondary incidents. Events can be classified into one of the cells in this table. They go from no secondary in the same or opposite directions to 2 or more same direction and opposite direction secondary incidents. Every event category will have some impact on urban traffic, with higher level categories having greater impacts on average.

Table 1: Categories for Events Showing Various Levels of Secondary Incidents

Secondary Incidents Abbreviation	0 Secondary incident in the opposite direction (Sod0)	1 Secondary incidents in the opposite direction (Sod1)	2+ Secondary Incidents in the opposite direction (Sod2+)
0 Secondary in the same direction (Ssd0)	Ssd0Sod0	Ssd0Sod1	Ssd0Sod2+
1 Secondary in the same direction (Ssd1)	Ssd1Sod0	Ssd1Sod1	Ssd1Sod2+
2+ Secondary in the same direction (Ssd2+)	Ssd2+Sod0	Ssd2+Sod1	Ssd2+Sod2+

Note: "Ssd" represents secondary incidents in the same direction; "Sod" represents secondary incidents in the opposite direction.

Identification Method for Secondary Incidents

To capture a cross-segment large secondary event and overcome the limitation of the segment-based method, a queue-based dynamic identification method was developed for the identification of secondary incidents in the same direction. For every incident, its queue length was calculated through a deterministic queuing model (D/D/1). If the queue length exceeded the length of the segment where the primary incident occurred, then the spatial boundary is extended to the adjacent upstream segment; if the queue still overflows this adjacent segment, then the spatial boundary goes further to the next upstream segment. This recursive process stops when the queue is accommodated. If an incident is covered by the spatial boundary and it is within the duration of the downstream primary incident, it will be identified as a secondary incident.

As noted earlier, the secondary incident identification also considers secondary incidents in the opposite direction. To identify these secondary incidents, the length of the opposite segment is set as the spatial boundary. If an incident in the opposite segment occurs within the duration of the primary incident, then it is considered a secondary incident in the opposite direction. To further emphasize visual distraction caused by the primary incident, this primary incident must meet several pre-defined conditions: it can be an accident, or a non-accident with its location is in the left shoulder, it blocks a lane, and it causes a queue backup, and there is no visual barrier in the median.

Primary Incident Analysis

To answer the question about what factors are associated with secondary incidents, they are characterized on a scale. On a continuum, event adversity can be conceptualized as ranging from single incidents to multiple secondary incidents (large-scale events). This research simplifies the scale to three levels that are ordinal and estimates a simple ordered logit model to explore the relationship with a set of independent variables. The event adversity scale is ordered according to incident types shown in Table 2. Not considering disastrous incidents, the impact of secondary incidents on traffic in an urban area is characterized as single adverse incident event (when there are no secondary incidents), two adverse incident events (if there is one secondary incident and its primary incident), and multiple adverse incident events (if there are multiple secondary incidents and their primary incident). Note that this characterization is for average events, recognizing that some single incidents can have major traffic consequences, which can exceed the impacts of average multiple secondary incident events. Furthermore, the structure presented in this paper lends itself to having more categories on the ordinal scale.

Table 2: Ordered Response Profile

Categories (J)	Event Types	Expected Event Adversity
1	Ssd0Sod0	Single incident event
2	Ssd0Sod1; Ssd1Sod0	Primary-secondary pair event
3	Ssd0Sod2+; Ssd1Sod1; Ssd1Sod2+ Ssd2+Sod0; Ssd2+Sod1; Ssd2Sod2+	Primary-multiple secondary incidents event (large-scale)

In an ordered logit model, category $j = 1$ is defined as the minimum level of variable, $j = 2$ is the next order level and so on for the total k categories ($k = 3$ in this case). The probability of a given observation Y above particular category j is calculated by equation (1):

$$P(Y_i > j) = \frac{\exp\left(a_j + X_i\beta\right)}{1 + \exp(a_j + X_i\beta)} \qquad j = 1, 2 \tag{1}$$

Where β represents the slope for explanatory variables X. β is a constant for all categories which follows a parallel line assumption. α_j is the intercept for j category. Response is coded as three-level ordinal secondary incidents. Explanatory variables include primary incident characteristics: incident type (e.g., Accident =1; Others =0), incident duration, the number of involved vehicles, lane blockage (Yes =1; No =0), truck/s involved (Truck =1; Non-Truck =0), out-state vehicle involved (Yes =1; No =1), road geometric information (segment length, the number of lanes, curvature (Curve =1; Straight =0)), and traffic data (e.g., AADT). The simple interpretation of the regression is that if β is positive, the probility towards multiple secondary incidents is higher with increasing value of the independent variable. Marginal effects are needed to get a clearer sense of associations.

STATA software was selected to perform this ordinal logit regression. Parallel line assumption test was performed by an add-in package *(11)*. If the parallel line assumption was violated, a generalized ordinal Logit/partial proportional model (gologit2) was used to conduct a further analysis *(12)*. This software ran an iterative process to estimate partially proportional odds model, where the parallel lines constraint was only relaxed for those unjustified variables. After gologit2 regression, the parameter estimates for the constrained variables were the same while the estimated unjustified β coefficients will be different for each category. In the mean time, marginal effects are computed as well.

Time to Secondary Events Analysis

To answer the question about time to secondary incidents, the actual time gap between a primary and secondary incident was calculated. This involves differentiating the start times of identified primary-secondary pairs. First, a simple curve fitting model was estimated to obtain the best fitting equations for time gap. This allowed us to examine the time-gap distribution. Second, the association of time gap with the characteristics of primary incidents is of interest. However, the observation of the time gap is conditional on the occurrence of secondary incidents. Heckman selection model *(13)* was used to capture this kind of conditionality. The structure of the model consists of an outcome equation with a sample selection equation as below:

$$\mathrm{Ln}(\Delta \mathrm{t}) = \alpha + \beta X \qquad \text{(Outcome: estimated time-gap)} \tag{2}$$

$$\mathrm{P(SEC} = 1) = \alpha' + \beta' X \qquad \text{(Selection: secondary incident occurs or not)} \tag{3}$$

Ln(Δt) represents the logarithm of the time gap. The log transformation was used to improve the statistical properties of the model.

RESULTS AND ANALYSIS

The identified secondary incidents for Hampton Roads are listed in Table 3. This table shows a frequency and percentage of secondary incidents along each direction. It is evident that I-64 (EB, WB), I-264 (EB, WB), I-564 (EB, WB) are problematic routes with high frequency and percentages of secondary incidents. Secondary incidents in the opposite direction mostly occurred on I-64 (EB, WB) and I-264 (EB, WB). This information would be valuable for incident management.

Table 3: Route-based Secondary Events Summary (2005 data)

Route (length in miles) \ Type		Ssd0 Sod0 Freq (%)	Ssd0 Sod1 Freq (%)	Ssd0 Sod2+ Freq (%)	Ssd1 Sod0 Freq (%)	Ssd1 Sod1 Freq (%)	Ssd1 Sod2+ Freq (%)	Ssd2+ Sod0 Freq (%)	Ssd2+ Sod1 Freq (%)	Total
I-64 (53)	EB	10158 (96.6)	51 (0.5)	1 (0.0)	257 (2.4)	7 (0.1)	0	37 (0.4)	5 (0.0)	10,516
	WB	9750 (97.4)	33 (0.3)	0	209 (2.1)	3 (0.0)	1 (0.0)	17 (0.2)	2 (0.0)	10,015
I-264 (25)	EB	6407 (96.7)	18 (0.3)	2 (0.0)	170 (2.6)	5 (0.0)	1 (0.0)	24 (0.4)	2 (0.0)	6,629
	WB	5670 (96.1)	30 (0.5)	2 (0.0)	178 (3.0)	6 (0.1)	0	16 (0.3)	1 (0.0)	5,903
I-664 (20)	NB	818 (99.2)	0	0	7 (0.8)	0	0	0	0	825
	SB	817 (99.6)	0	0	3 (0.4)	0	0	0	0	820
I-464 (5.8)	NB	458 (95.7)	0	0	1 (0.2)	0	0	0	0	459
	SB	535 (99.6)	0	0	2 (0.4)	0	0	0	0	537
I-564 (2.9)	EB	286 (95.7)	0	0	11 (3.7)	0	0	2 (0.7)	0	299
	WB	413 (97.4)	0	0	9 (2.1)	0	0	2 (0.5)	0	424

Note: "Ssd" represents secondary incidents in the same direction; "Sod" represents secondary incidents in the opposite direction. "Freq" is the secondary incident frequency and "(%)" is the corresponding percentage in the total counts at each route-bound.

Primary Incident Analysis

Table 4(a & b) show ordered logit models that explain event adversity. The first model is a simple ordinal regression (proportional odds model) based on restrictive assumptions about the estimated parameters. The model in Table 4(b) is a generalized ordered logit model with relaxed restrictions placed on model parameters that are applicable to various event adversity levels. More technically, the Brant test for simple ordinal regression showed that the assumption of the parallel lines model is violated. The main variables of interest in this case are the number of vehicles involved and lane blockage. Thus a generalized ordered logit model was used to relax the constraint to re-estimate β parameters which were summarized in Table 4(b).

Summary statistics shows that both models are statistically significant (5% level). The constants for these models are only used to estimate response probability. In the coefficients columns, the parameter estimates for constrained variables are the same in the two sets of β. Only the number of vehicle involved and lane blockage were re-estimated. Effects of the constrained variables in Table 4(b) can be interpreted to be the same as the first simple ordinal regression model in Table 4(a). A positive β indicates that higher values of the explanatory variable are associated with higher (secondary) event adversity. Both models show that accident, longer incident duration, more involved vehicles, more lanes, longer segments, and higher AADT are associated with higher occurrence of secondary incidents. Note that primary incident duration is a tricky variable, in the sense that response and clearance times may be longer if there are secondary incidents involved. Trucks were expected to make a positive contribution to higher scale events, but the variable was not statistically significant (5% level). Out-of-state vehicle surprisingly showed a negative relationship with the likelihood of adverse events, but it is not statistically significant. The variable curves also made a non-significant contribution to reduce adverse events. The difference between the two models is that the partial proportional odds model accounts for unequal contributions of explanatory variables to different categories. The number of vehicle involved and lane blockage in Table 4(b) are such variables. They are significantly associated with the higher event adversity (more secondary incidents). Specifically, they have a greater effect in the higher category than in the lower category. That means that more vehicles involved and lane blockage in the primary incident will more likely lead to multiple secondary incidents.

Table 4(a): Proportional Odds Model for Ordinal Scale of Events

	Generalized Logit Model (ologit)			
Parameters	**Coefficients**	**Marginal effects**		
	β	**Ssd0Sod0**	**Ssd1~0Sod1~0**	**Ssd2+~0Sod2+~0**
Primary Incident Characteristic				
Accident	0.6594475***	-0.0168842	0.0150542	0.0018300
Incident Duration	0.0226608***	-0.0004399	0.0003929	0.0000470
Truck Involved	0.0253337	-0.0004974	0.0004442	0.0000532
Number of Vehicles	0.2990548***	-0.0058053	0.0051845	0.0006207
Outstate Vehicle	-0.0224628	0.0004328	-0.0003866	-0.0000463
Lane Blockage	0.6670955***	-0.0175416	0.0156376	0.0019040
Road Geometry				
Segment Length	0.1521862**	-0.0029542	0.0026384	0.0003159
Number of Lane	0.2249527**	-0.0043668	0.0038999	0.0004669
Curve	-0.0265283	0.0005155	-0.0004603	-0.0000551
Traffic				
AADT/1000	0.0081377***	-0.0001580	0.0001411	0.0000169
Constant	6.079981			
	8.351472			
Number of observation = 34209				
Log likelihood function = -4213.9652			LR chi2(10) = 1389.56	
Pseudo R2 = 0.1415			Prob > chi2 = 0.0000	

Note: * p <0.10, ** p<0.05, ***p<0.001

Table4(b): Partial Proportional Odd Model for Ordinal Scale Events

Parameters	Generalized Logit Model				
	Coefficients		Marginal effects		
	Ssd0Sod0	Ssd1~0Sod1~0	Ssd0Sod0	Ssd1~0Sod1~0	Ssd2+~0Sod2+~0
Primary Incident Characteristic					
Accident	0.6862004***	0.6862004***	-0.0178419	0.016546	0.0012961
Incident Duration	0.0225925***	0.0225925***	-0.0004402	0.0004087	0.0000315
Truck Involved	0.0337599	0.0337599	-0.0006678	0.0006200	0.0000478
Number of Vehicles	0.2633648***	0.4960111 ***	-0.0051314	0.0044398	0.0006916
Outstate Vehicle	-0.0144579	-0.0144579	0.0002804	-0.0002603	-0.0000201
Lane Blockage	0.6321334***	1.238747***	-0.0164095	0.0131970	0.0032124
Road Geometry					
Segment Length	0.1525513**	0.1525513**	-0.0029723	0.0027596	0.0002127
Number of Lane	0.2233458**	0.2233458**	-0.0043517	0.0040403	0.0003114
Curve	-0.025995	-0.025995	0.0005070	-0.0004707	-0.0000363
Traffic					
AADT/1000	0.0079976***	0.0121956***	-0.0001558	0.0001388	0.0000170
Constant	-6.025443***	-8.847404***			

Number of observations = 34209
Log likelihood function = - 4195.5676 LR chi2(11) = 1426.35
Pseudo R2 = 0.1453 Prob > chi2 = 0.0000

Notes: * p <0.10, ** p<0.05, ***p< 0.001; Marginal effects in the two tables represent the changes in the dependent variable with a unit change in the independent variable. STATA software procedure glogit2 was used with autofit.

Time to Secondary Events Analysis

Time-gap Distribution

Curve fitting *(14)* was performed to explore the time gap distribution between incidents. The time gap data sets used for analysis are: 1st secondary incident, 2nd secondary incident in the same direction and 1st secondary incident in opposite direction. After curve fitting the data using several built-in models in MATLAB 2007, the fitting statistics: the goodness of fit was used to determine the best fitting model. As a result, the second order Gaussian model was selected. Mathematically it can be expressed as:

$$y = a_1 \times e^{\left(-\left(\frac{x-b_1}{c_1}\right)^2\right)} + a_2 \times e^{\left(-\left(\frac{x-b_2}{c_2}\right)^2\right)} \quad (4)$$

This analysis describes the full distribution of possible time-gaps. Three corresponding sets of histogram plots, probability density fitting curve and cumulative probability curves are presented in Figure 3. Within 20 minutes, more than 60% of 1st secondary incidents, and 50% of

1st opposite direction secondary incidents, and around 30% of 2nd secondary incidents would occur. Within 10 minutes, 40% of 1st secondary, 15% of 2nd secondary and 25-30% of 1st opposite direction secondary incidents occur. Compared with time-gap distributions of 1st secondary incidents and 1st secondary incidents in the opposite direction, the time gaps of 2nd secondary incidents are more widely spread. These results provide a quantitative assessment of relative changes of incident frequency with time. This provides a useful reference for incident management to determine critical clearance times and its benefit potentially preventing an incident from becoming an adverse (large-scale secondary) event.

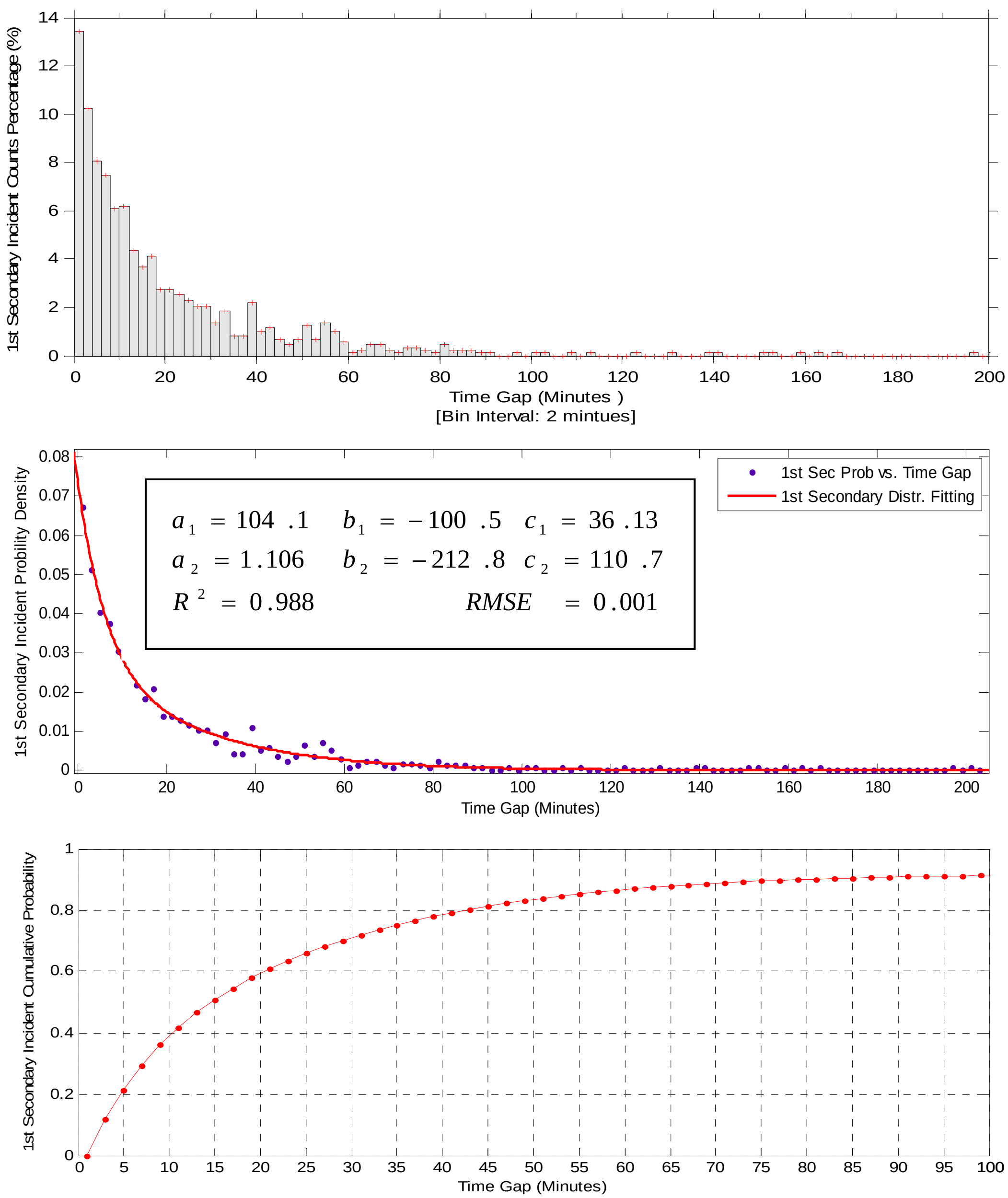

Figure 3 (a): Time Gap of 1st Secondary Incident in the same direction

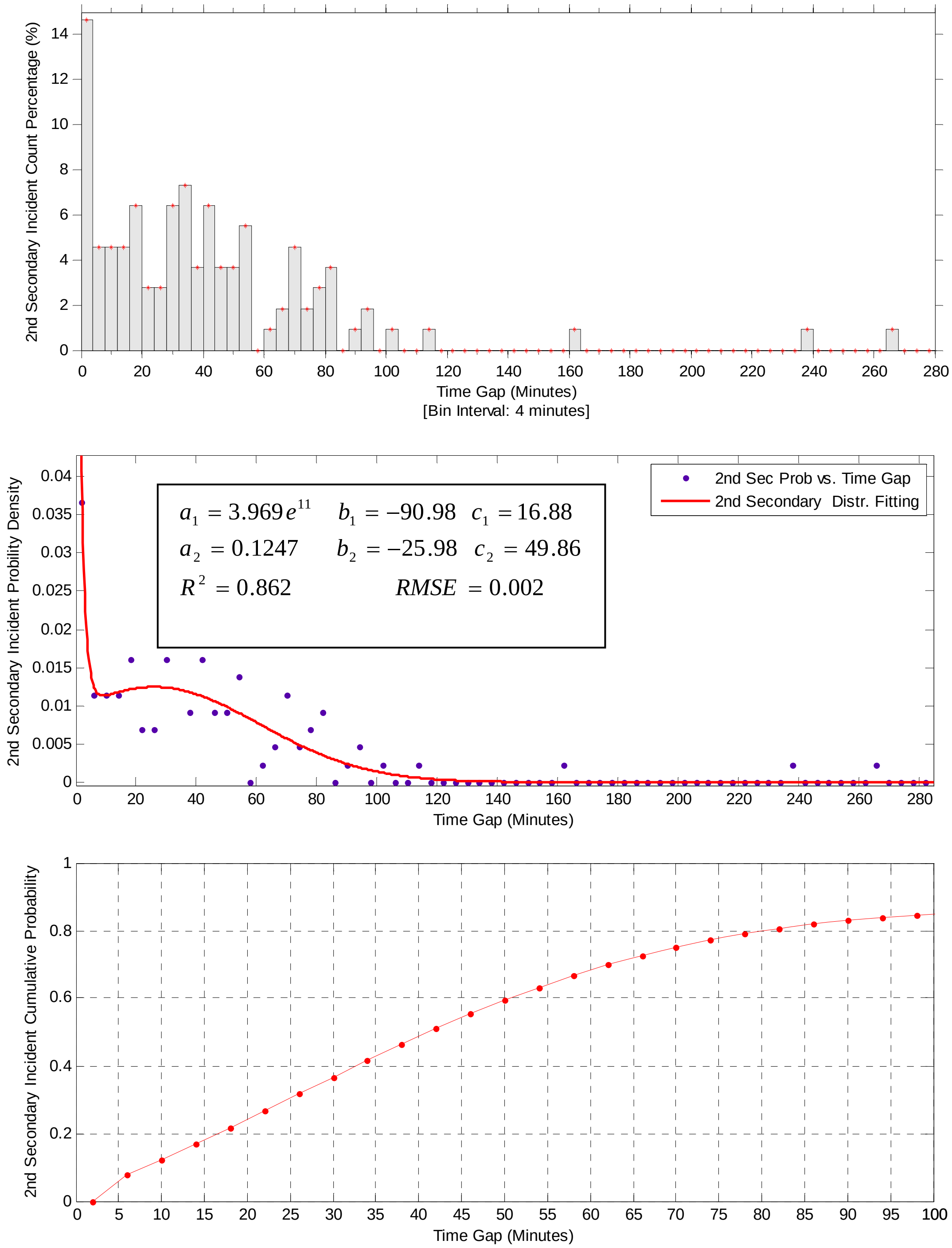

Figure 3(b): Time Gaps for 2nd Secondary Incident in the same direction

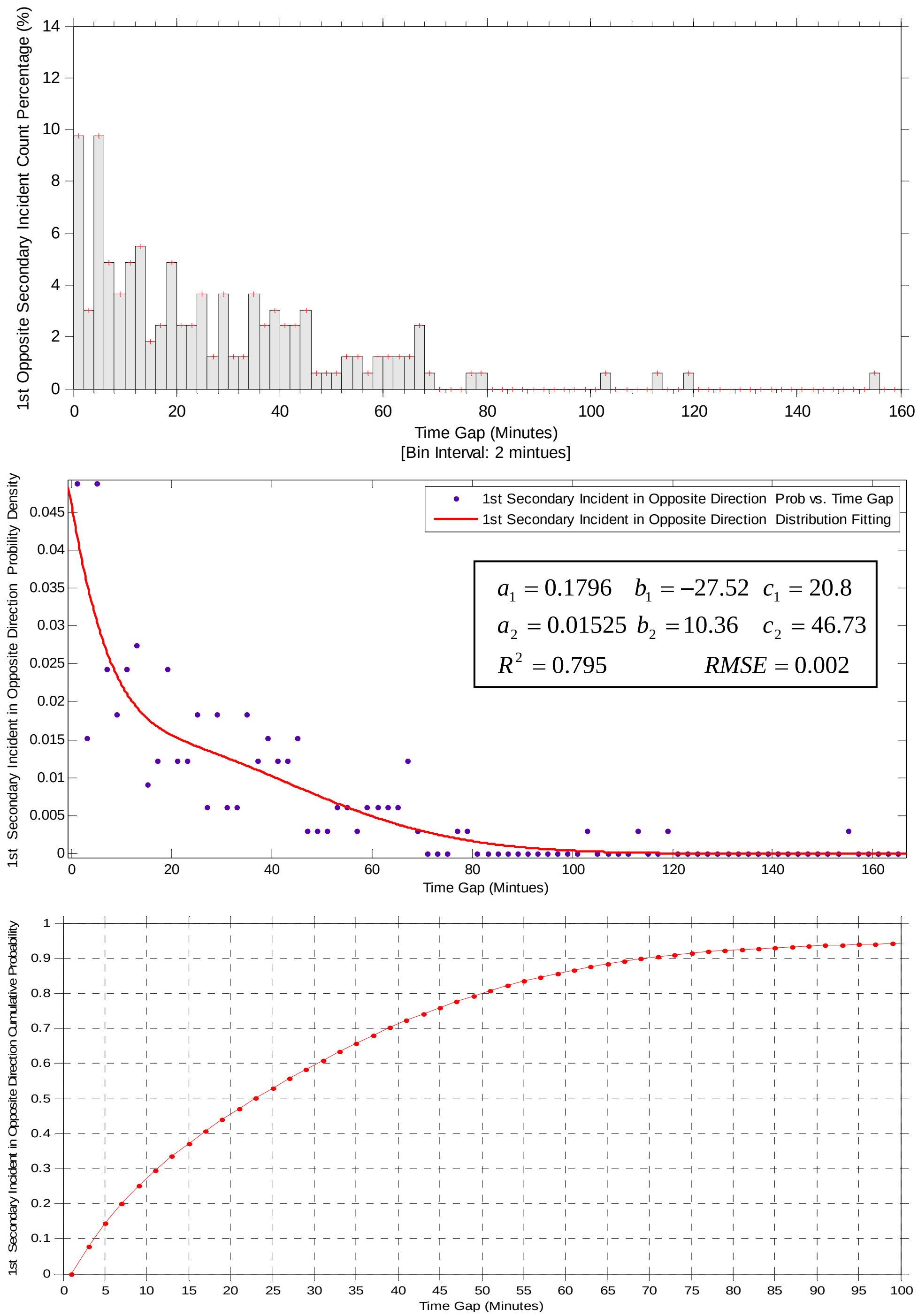

Figure 3(c): Time Gap for 1st Secondary Incident in the opposite direction

Heckman Model Results

The results from Heckman model for time to the first secondary incident are summarized in Table 5. Models for the other two categories (2nd secondary incident and 1st secondary incident in the opposite direction) could not be estimated using the Heckman selection procedure due to their small sample size. The reported model is statistically significant overall (Wald $\chi^2 = 742.90$, p-value <0.001) and the statistics show that conditionality should be taken into account ($\chi^2 = 742.90$ and p-value < 0.001). The selection model shows that the occurrence of the first secondary incident is positively associated with incident type (accident), long incident durations of the primary incident, involvement of multiple vehicles, lane blockage, long segment length, segments with more lanes and high traffic volumes. In addition, based on estimated marginal effects, it is evident that lane blockage shows a substantial effect on secondary incident occurrence. Note that if a secondary incident occurs shortly after the primary, it can lead to longer incident durations due to additional impedance—so there is interdependency, which was not explored in this context (15).

The time to first secondary incident is modeled to have an exponential relationship with the explanatory variables, as a log transform is taken. The time to secondary incident is shorter if the primary incident is an accident, the primary incident has a longer duration, the primary incident causes lane blockage, and roadway has long length, more lanes and higher traffic. The outcome equation can be used to predict the time-gap of the first secondary incident.

Table 5: Heckman Model for Time Gap

Parameters	Heckman Selection Model (Logit Link)		
	Coefficients		Marginal effects
	Outcome	Selection	Pr(Sec1=1)
	LN(Time Gap)	P(Sec1=1)	
Primary Incident Characteristics			
Accident	-0.24137	.0933572*	.0045283
Incident Duration	-0.01008 ***	.0116952***	.0005225
Truck Involved	-0.00129	.0054804	.0002449
Number of Vehicles	0.58004 ***	.1571563***	.0070217
Out of state Vehicle	0.047175	-.0212049	-.0009474
Lane Blockage	-1.06316 ***	.3030384***	.0180753
Road Geometry			
Segment Length	-0.11721*	.0401892***	.0017956
Number of Lane	-0.26308**	.0773715**	.0034569
Curve	-0.00558	.0010218	.0000456
Traffic characteristics			
AADT/1000	-0.01084***	.0032279***	.0001442
Constant	12.53511***	-2.957001***	
Number of obs = 37015 Log likelihood = -5185.16 Wald chi-squared(10) = 212.32		Censored obs = 36059 Uncensored obs = 956 Prob > chi-squared = 0.00	
LR test of independence of equations. (Rho = 0), chi-squared = 794.9, Prob>chi-squared = 0.000			

Note: * p <0.10, ** p<0.05, ***p<0.001

CONCLUSIONS

This paper contributes to the transportation research by answering fundamental research questions about secondary incidents. While such incidents are relatively rare, they can stretch the resources of responding agencies, especially transportation agencies. This research characterizes events as primary incidents and secondary incidents in the same and opposite direction. Roadways that are likely to have multiple secondary incidents (large-scale events), were identified by visualizing the frequency and percentage of secondary incidents. A deeper understanding of the factors that are associated with the occurrence of secondary incidents was developed through rigorous modeling. Furthermore, the time to secondary incidents was analyzed. Finally, the implications for incident management are explored.

First, a queue-based methodology was developed to identify adverse events, especially for capturing secondary incidents over multiple segments. This method overcomes the limitations of at least some earlier studies that have used a fixed spatial boundary. Moreover, secondary incident in the opposite direction were also identified in this study. After identification of events that involved multiple secondary incidents, problematic routes were identified in terms of high frequency and percentage of secondary incidents.

Second, events were characterized as having different adversity levels on an ordinal scale. Two ordered logit models estimated the associations with various factors. Based on primary incidents characteristics, accident and long durations were found to increase the frequency of secondary incidents associated with a primary incident. More importantly, multiple-vehicle involvement and lane-blockage had a different contribution to the occurrence of secondary incidents, and they are particularly associated with more secondary incidents. Road geometry such as the number of lanes, length of segment and high traffic also were associated with more secondary incidents.

Third, to investigate the temporal distribution of secondary incidents, the actual time gaps between identified secondary incidents and their primary incidents were calculated. A distribution was fitted to time-gaps. After examining distributions for three categories: the first secondary incident in the same direction, the first secondary incident in the opposite direction and the second secondary incident in the same direction, it was observed that more than half of the first two category incidents occurred within 20 minutes of the primary incidents occurrence. But the time gap distribution of 2^{nd} secondary incident category was relatively widely spread. This implies that the time gaps of second secondary incidents are more difficult to predict and they bring greater uncertainty in incident management. A Heckman model was estimated to investigate the relationship between time-gap and primary incident characteristics. The time to the first secondary incident is shorter if the primary incident is an accident, the primary incident has long duration, lane blockage occurs or there are multiple lanes and higher traffic levels.

From an incident management perspective, the above results have certain implications. First, comprehensive adverse event identification can aid in evaluating route safety situations in terms of secondary incident occurrence. Second, quantified effects of key factors that include roadway geometry and incident characteristics help reduce the likelihood of a secondary incident occurrence. Especially, multiple vehicles involvement and lane blockage are two major contributors to occurrence of more secondary incidents. Finally, a deeper understanding of the time-gap analysis helps select critical clearance times and assess its potential benefit to operating an effective safety service patrol operation. Large-scale adverse events (with 2 or more secondary incidents) need further attention. We suggest that urban area traffic operations centers identify in their data whether an incident is secondary depending on field reports and whether or not the incident was related to queues from an upstream incident. This will certainly facilitate analysis of large-scale adverse events. Secondly, we suggest using a case-based approach, where each large-scale event is studied closely, and lessons are learned.

REFERENCES

1. Skabardonis, A., Noeimi, H., Petty, K. F., Rydyzewski, D., Varaiya, P., Al-Deek, H., Freeway Service Patrol Evaluation. UCB-ITS-PRR-95-5, Berkeley, CA, 1995.
2. Ozbay, K. and P. Kachroo, Incident Management in Intelligent Transportation Systems. Artech House Publishers, MA, 1999.
3. Kwon, J., M. Mauch, P. Varaiya, The Components of Congestion: Delay from Incidents, Special Events, Lane Closures, Weather, Potential Ramp Metering Gain, and Excess Demand. 85th TRB Annual Meeting, 2006.
4. Raub, R. A. 1997. Secondary Crashes: An important component of Roadway Incident Management. Transportation Quarterly 51.3, pp. 93–104.
5. Karlaftis, M. G., Latoski, S. P., Richards, N. J., Sinha, K. C. ITS impacts on safety and traffic management: an investigation of secondary crash causes. Intelligent Transportation Systems Journal 5 (1), 39-52, 1999.
6. Moore, J. E., Giuliano, G., S., Cho, Secondary accident rates on Los Angeles freeways. Journal of Transportation Engineering 130 (3), 2004, 280-285.
7. Hirunyanitiwattana, W. and S. Mattingly. Identifying Secondary Crash Characteristics for California Highway System. 85th TRB Annual Meeting. 2006.
8. Zhan, C., Shen, L., Hadi, M., Gan, A. Understanding the Characteristic of Secondary Crashes on Freeways. 87th TRB Annual Meeting, 2008.
9. Sun, C. and Chilukuri, V. Secondary Accident Data Fusion for Assessing Long-Term Performance of Transportation Systems. Report No. MTC Project 2005-04, 2007.
10. Teng, H., Masinick J. P., An Analysis on the Impact of Rubbernecking on Urban Freeway Traffic. Report No. UVACTS-15-0-62, 2004.
11. Long, J. S. and Freese, J. Regression Models for Categorical Dependent Variables Using Stata. 2nd Edition, Stata Press. 2006.
12. Williams, R. Generalized Ordered Logit/Partial Proportional Odds Models for Ordinal Dependent Variables. The Stata Journal 6(1):58-82, 2006.
13. Heckman, J. The common structure of statistical models of truncation, sample selection, and limited dependent variables and a simple estimator for such models. Annals of Economic and Social Measurement 5: 475-492. 1976.
14. The MathWorks, Inc, MATLAB version1.2(R2007b) Curve Fitting Techniques, 2007.
15. A. Khattak, X. Wang, H. Zhang, Are incident durations and secondary incident occurrence interdependent? Accepted for presentation at the Transportation Research Board, National Academies, Washington, D.C., 2009.