Crash Risk Reduction at Signalized Intersections Using Longitudinal Data

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16. Abstract

This study extends the previous work of Burkey and Obeng (2004) that examined the impact of red light cameras on the type and severity of crashes at signalized intersections in Greensboro, NC. The extension takes the following form. First, we extend the data to cover 57 months, and to include demographics, technology variables, the condition of a driver at the time of the crash, vehicle characteristics, land use and visual obstruction. Second, instead of examining the impact of red light cameras, we focus on identifying the determinants of crash severity, two-vehicle crashes, and property damage costs. The major findings are that the safety impacts of seatbelt use outweigh the impacts of airbags deploying because the latter tends to increase evident injuries and property damage costs, while the former reduces these injuries. We also find that head-on collisions and under rides increase evident injuries. For two-vehicle crashes, we find that the risk of severe injuries increases in pickup-pickup crashes and SUV-pickup crashes, while the risk of possible injuries increases in car-truck crashes. For property damage costs, we found the condition of the driver at the time of the crash (i.e., illness, impaired, medical condition, driver falling asleep, driver apparently normal) to be important determinants in increasing these costs. The types of accidents that we found to increase property damage costs are running into a fixed object and under rides. Finally, we found that property damage costs of crashes are low where the land uses are commercial and institutional suggesting that the accidents that occur in these areas are minor.

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TABLE OF CONTENTS

LIST OF TABLES

EXECUTIVE SUMMARY

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1. INTRODUCTION

Problem Statement: Nearly half of all accidents in the U.S. occur at or near intersections. Consequently, many specific studies have been conducted that investigate how various aspects of intersections relate to safety and accident rates. One such aspect is automated enforcement of traffic signals using cameras, i.e., red light cameras, which is a major new initiative used by many urban areas to reduce red light running and improve safety. At this point, the conclusion that red light cameras (RLCs) reduce accidents is based on sparse and primarily anecdotal evidence. McFadden and McGee (1999) concluded that, while reductions in violations, cost savings, and public acceptances are all benefits from their use, "Additional crash data are needed to validate and quantify the RLCs automated enforcement programs implication on crashes" (p. 27). Further, a recent review of studies on red light cameras by McGee and Eccles (2003) raises questions about the results of the studies. This is because these authors found that many of the studies were not well-designed, lacking well-selected control groups, and used little data.

Burkey and Obeng (2004) tried to resolve some of the problems with the earlier studies by using a large data set for Greensboro, North Carolina, with some degree of success. Working with the traffic-engineering department of the City of Greensboro and the North Carolina Department of Transportation, these researchers collected and analyzed a large data set on intersection accidents that include red light cameras as a variable. In their final data were 7,581 accidents that occurred at 302 signalized intersections over 45 months. Some of the data were on traffic counts (average daily volume), the presence of red light cameras, all red time, amber time, right turn signal, left turn signals, pedestrian crossing signal, number of lanes, left and right turn lanes, medians, and sidewalks. Others were types of accidents (e.g., rear-end collisions, front to side impacts), severity of accidents (e.g., fatality), types of vehicles involved, snowfall and precipitation, when the accidents occurred, and when a red light camera was placed at each intersection. These authors found that red light cameras did not appear to reduce accidents at intersections, but were associated with higher rates of accidents.

Objective: The present study extends the work of Burkey and Obeng (2004) in three main ways. First, it expands the data set to include a longer time span, updating the data from 45 months to 57 months. Second, it expands the data to include property damage costs, demographic information about drivers, the predominant land use at intersections, possible visibility problems at intersections that contributed to a crash, the conditions of vehicles' drivers at the time of accidents, and vehicle information (e.g., type of vehicle, estimated travel speed at impact, seat belt usage, airbag deployment). An additional, though minor, focus of this project is the efficacy of red light cameras by including appropriate new variables in the analysis. Thirdly, this study expands the analysis to investigate not only the determinants of accident rates, but also the determinants of accident severity given that an accident has occurred. This is done in three ways. First, a property damage cost model is developed to identify the predictors of damage cost produced in an accident. Second, a severity model is developed to identify the predictors of severe accidents (e.g. fatal, severe injury, or property damage only). Lastly, the study employs a recently developed technique to analyze the determinants of injury severity in two-vehicle crashes. This new technique is bivariate Poisson, which allows various types of injuries to be simultaneously estimated and correlated with one another.

Organization: The rest of the report is divided into seven sections. In Section 2, we present a review of the relevant literature that bears on this study, followed by a description of the data in Section 3, and an analysis of crash severity in Section 4. Section 5 deals with the determinants of injuries in two-vehicle crashes, Section 6 deals with land use and visibility effects on crashes, and Sections 7 and 8 deal with the determinants of property damage costs and conclusions, respectively.

2. LITERATURE REVIEW

Of the 6,394,000 automobile crashes in the U.S. in the year 2000, about 44% occurred at intersections or were classified as "intersection-related." Of these, 47% occurred at intersections with traffic signals (NHTSA, Traffic Safety Facts 2000). The nature of intersections poses a special set of dangers for vehicles, pedestrians, and bicyclists. For vehicles, intersections are likely to involve dangerous "angle" crashes where little protection is given to drivers and occupants, and rear-end collisions where whiplash injuries are common. Approximately 22% of fatalities and 46% of injuries to pedestrians occur at intersections.

The Advocates for Highway Safety (2001) suggest nine main ways to improve intersection safety:

1) Changes to or installation of appropriate static traffic control devices
2) Installing traffic signals
3) Proper timing of traffic signals
4) Installing dedicated turning lanes
5) Removing sight distance restrictions
6) Use of roundabouts
7) Use of Intelligent Transportation Systems (ITS)
8) Automated enforcement of red light running
9) Better signing such as larger, brighter stop, yield, and speed limit information

Within these nine suggestions are components that deal with structural changes, law enforcement, and conveying information to drivers. The standard protocol of most modern traffic-safety campaigns focuses on the “Three E’s”: Engineering, Enforcement, and Education.

Tarawneh et al. (2001) found that an education campaign significantly increased drivers’ understanding of traffic laws associated with red-light running. However, the Insurance Institute for Highway Safety (IIHS) (2001) criticizes the role of education in increasing safety and believes that engineering and enforcement efforts are much more important. Many times enforcement efforts are done on a high intensity but discontinuous basis (often called a “blitz” approach). These efforts can significantly affect safety, but are too costly to be used continuously. However, a low level of targeted enforcement can have large benefits. In Australia, several areas have been using Random Road Watch programs. These programs randomly monitor areas of roadway for two-hour periods using marked patrol cars. The intensity of the effort is chosen at a level that can be sustained over the long run and has been found to reduce accidents significantly, particularly fatal crashes (down 31%) (Newstead et al., 2001).

When analyzing strategies for safety improvements on roadways, one must first establish that a given strategy will produce the desired results. Occasionally, the goals of a safety program are measured in terms of compliance with the law. This is often the case with seatbelt programs, speed-reduction programs, and child-safety-seat programs. However, the underlying goal should never be ignored, which is to reduce crashes and the resulting fatalities, injuries, and property damage.

Once a strategy is known to increase safety, good estimates of the extent of its benefits should be made for various types of its applications. The main purpose of quantifying the benefits is so that reasonably accurate studies of efficiency can be made. Except on social or political grounds, a strategy is of no practical value if its costs exceed the benefits gained, or if a strategy with similar benefits can be implemented with lower costs. The most obvious benefits to a safety program are reductions in fatalities, injuries, and property damage. The most common method of classifying injuries and accidents is the KABCO method, which categorizes accidents and injuries as:

K: Killed
A: Incapacitating or Disabling Injury
B: Not Incapacitating, but Evident, Injury
C: Possible Injury,
O: No Injury, Property Damage Only (PDO)

It must be understood that accident classification and estimates of property damage amounts are somewhat subjective and normally determined by a police officer at the scene. In the present study, we use the KABCO system as reported in our accident data. To compare severity between different types of accidents, it is sometimes convenient to attach a dollar value to each type of accident or injury. In October 1994, the FHWA issued a list of "Comprehensive Cost Estimates," listed in Table 1. These values were updated to 2002 dollars by the investigators of this project.[1]

Table 1: Comprehensive Costs of Crashes

Severity	Description	FHWA (1994)	FHWA (2002)	NCDOT 2001
K	Fatal	$2,600,000	$2,979,600	$3,300,000
A	Incapacitating	180,000	206,280	200,000
B	Evident	36,000	41,256	57,000
C	Possible	19,000	21,774	27,000
PDO	Property Damage Only	2,000	2,292	3,900

Also listed in Table 1 are "Standardized Crash Cost Estimates for North Carolina," issued in December 2001, by the NCDOT (Troy, 2001). The values determined in this report are termed "comprehensive," in that they include estimates of medical, work loss, employer costs, traffic delay, property damage, and changes in quality of life. Though these cost estimates were issued in 2001, they are measured in terms of year 2000 dollars. In addition

[1] This is updated using GDP Implicit Price Deflator from Q1, 2002.

to accident reductions, other possible benefits or costs of implementing safety programs are changes in delays at intersections, resulting in effective increases or reductions in road capacity. These changes affect travel times for roadway users and they should be counted properly in benefit/cost ratios. While reducing speed limits may increase safety but reduce capacity, there are safety efforts that have also been shown to increase capacity. For example, efficiently programming traffic control devices in a network can yield benefits in reduced delays and reduced fuel use, as well as increased safety (Skabardonis, 2001).

Another important consideration is that very few safety improvement projects are undertaken randomly, as would be required for an unbiased estimate of the effects. Most often, safety efforts are directed toward intersections or roadways that have the highest accident rates in a given time period. Ceteris paribus, an intersection with an unusually high accident rate in one period is likely to have a lower (more average) rate in the next. This phenomenon is sometimes called the “regression to the mean effect.” Thus, the effects of a safety program targeted in this way may be overstated. Kulmala (1994) found that accidents declined approximately 20% due to regression to the mean effects, independent of any safety measures implemented. If ignored, regression to the mean effects can easily mislead researchers to inappropriately attribute crash reductions to an ineffective safety program.

In addition, the quality of the data used in safety studies must be ascertained. One often overlooked aspect of accident data is censoring. One must realize that not all accidents are reported and state laws differ on reporting requirements. In North Carolina, the crash-reporting threshold is currently $1,000. That is, if a police officer is called to the scene of an accident, the officer is not required to make a report of the details of the accident unless he or she estimates that the damage is in excess of $1,000 or if there is injury. Therefore, many accidents are never entered into a crash database and this may affect the results of accident studies if ignored. The research related to this subject has been sparse. Zegeer et al. (1998) studied the differences in various types of accidents that would be reported under three different types of reporting thresholds: traditional (value), tow away, and injury. They found that using higher thresholds (tow away versus traditional, for example) tends to seriously underreport certain types of crashes. One would expect that the traditional thresholds lead to similar types of bias in accident reporting.

In this study, we analyze four main questions:

1) What crash-level factors can help explain injury severity?
2) What crash-level factors can help explain property damage levels?
3) What vehicle-level and driver characteristics determine injury severity levels in two-vehicle crashes?
4) What roles do land use and visibility problems play in determining accident rates at intersections?

In the next section, we describe the data set used for this report.

3. DATA

Context

The focus of this research is the City of Greensboro, North Carolina. With the cooperation of the Greensboro Department of Transportation (GDOT), and NCDOT, we collected most of the data on accidents and the characteristics of intersections with stoplights in the city. The data include demographic information, driver condition, land use, vehicle use, and economic variables that were obtained from the Safety Information Management and Support Section of North Carolina Department of Transportation (NCDOT). This section of the NCDOT is responsible for acquiring and compiling accident data from police reports, and entering them into computerized databases called the "Traffic Engineering Accident Analysis System" (TEAAS). The data are primarily contained in three types of files. The Occupants file contains information on those in the vehicles at the time of the crash. The Event-Level data contains one record for each accident, including location, number of vehicles involved, numbers of injuries, and other data. Lastly, the Unit-Level data contains one record for each vehicle involved in each accident. Each record details the type of vehicle, damage estimates, injury levels, indications of use of alcohol, drugs or seatbelts, and many other variables. We used the Event-Level data and organized them based upon the routes where the accidents occurred, and matched them with intersections. Additionally, we combined this information with the Unit-Level data. Thus, the data is organized by each vehicle involved in an accident at a signalized intersection. Specific details of this data follow.

Independent variables

1. *Signalized intersection characteristics*: Previous studies shed light on those intersection characteristics that explain the probability of an accident occurring. These characteristics include the length of amber time, red time, number of lanes, pedestrian signals, medians, and no turn on red signals. For example, Burkey and Obeng (2004) found that these variables are differently associated with various types and severities of accidents. We include data on these variables in the present study.
2. *Traffic and road characteristics*: The probability of an accident occurring is very much related to both traffic and road characteristics. Traffic volume, for example, has been used in analyses of highway safety/fatalities (Michener and Tighe, 1992), as have traffic volume per lane (Milton and Mannering, 1998) and posted speed limits (McCarthy, 1994). Furthermore, Keeler (1994) found differences in the signs of speed limits on rural and urban roads, which he attributes to offsetting behavior and the ease of evading speed limits in rural areas. In addition to these variables, our data include the estimated speed of each vehicle in the accident, the speed of each vehicle at the time of impact, and the condition of the road (whether wet or dry).
3. *Land use characteristics*: The type of land use at an intersection could affect crashes and therefore highway safety. Commercial and retail activities are major traffic generators and increase the exposures of drivers to accidents, especially accidents involving turning vehicles. Similarly, entrances to residential areas are major accident points. To capture these land use effects, our model includes binary variables for the following land uses: residential, institutional, commercial, and industrial.
4. *Driver characteristics*: Numerous studies shed light on the effect of driver characteristics on accidents. While previous studies on health and safety found income (Peltzman 1975, Keeler 1994) and the proportion of young people (Cook and Tauchen, 1982) as relevant in explaining highway accidents, recent studies focus on the physical condition of the driver as a major contributor of crashes. This is because it has been found that drivers under the influence of drugs and alcohol or who become ill while driving are involved in some of the most fatal highway accidents. Our data includes information on gender, driver license restriction

(corrective lenses, daylight driving, 45-miles-per-hour driving, no interstate driving), and driver impairment (alcohol and/or drugs suspected).

5. *Technology variables*: The probability of an accident occurring and its severity depend upon the technological features of the intersection such as the presence of a red light camera. In addition, they depend upon the technological features of the vehicles and whether or not those features deployed at the time of accidents. For example, ABS brakes are known to reduce stopping distances and could reduce accidents in the absence of offsetting behaviors by drivers. However, while airbags and shoulder belts may reduce injuries, they do not reduce accidents. The effects of these technological variables are examined in this research. These technological variables include shoulder and lap-belt use, only lap-belt use, only shoulder-belt use, airbag deployed/not deployed, airbag deployed on side, and airbag deployed front and side. Also, we include the presence of a red light camera at an intersection in the analysis.
6. *Vehicle type*: The severity and damage from highway crashes depend upon the types of vehicles involved. More severe accidents and property damage occur when accidents involve passenger cars and heavier vehicles such as trucks, sports utility vehicles, and vans. In accidents involving passenger cars and sports utility vehicles, for example, it is possible for over/under rides to occur and result in fatalities. In related research, Bedard et al. (2002) studied the impact of driver impairment, speed, vehicle deformity, airbag deployment, and vehicle weight on driver fatalities. They used odds ratios and logistic regression to explain factors that increase the likelihood of a driver fatality. Kockelman and Kweon (2001) used ordered probit models to investigate the severity of injuries in different types of vehicles. They found that light trucks and SUVs are more dangerous in single-vehicle accidents. In addition, they found that these vehicles are safer for the occupants involved in a multi-vehicle crash, but are more dangerous for occupants of other vehicles. Acierno et al. (2004) studied the impact that differing vehicle types can have on the type and severity of injuries. For example, when a passenger vehicle is hit by a LTV (Light Truck Vehicle[2]), the risk of injuries is higher. When hit in the side, head and upper thorax injuries are common, and the risk of death is 27-48 times greater than if the vehicle was hit by a passenger car. When hit head-on, injuries to lower extremities

[2] SUVs, Pickup Trucks and Minivans.

are common in addition to upper-body injuries, and are 3-4 times more likely to be fatal (compared to an accident with a passenger car). To account for the effects of different types of vehicles, our data identifies the types of vehicles involved in each accident. Specifically, the data identifies the following types of vehicles: passenger cars, light trucks, single unit trucks, vans, sports utility vehicles, and others.

7. *Environmental variables*: Weather conditions affect the probability of a crash occurring and severity of crashes. Rainfall, for example, increases stopping distances and the probability of an accident occurring. Heavy crosswinds, snowfall, and sleet also affect crashes. In our previous study (Burkey and Obeng 2004), we found both rainfall and snowfall have significant effects on crashes. However, regarding snowfall it was found that its relationship with crashes at intersections is negative, which we attributed to business and school closures in Greensboro during snowfall that removes traffic from streets and highways. This finding suggests that the effect of snowfall on crashes may depend upon location and frequency of snowfalls. The environmental variables included in this study are those related to weather (snow, rain, sleet, fog, cloudy, clear), and others that may obstruct vision (sunlight, trees, buildings, and vehicles).

Dependent variables

Consistent with the objectives of this study, the dependent variables are the severity of accidents and the cost of accidents. For severity, we distinguish between four types of crashes. They are those that cause fatalities, incapacitating injuries, evident but not incapacitating injuries, and possible injuries. A separate model is developed to explain each of the four types of severe accidents. For the cost of accidents, we use two dependent variables. The first is the estimate of property damage cost in the police accident reports. This property damage cost is approximate. However, under the assumption that errors in this cost are independent of the explanatory variables, we can use it in our equations. Police officers are required to file a complete accident report providing damage estimates if the property damage is at least $1,000 or if an injury occurred. Our data show many property damage estimates of less than $1,000, suggesting that those accidents involved injuries.

Table 2: Descriptive Statistics

Variable	Mean	Std.Dev.	Minimum	Maximum	Cases
Estimated damage $	2259.3314	2144.1438	0.0000	19000.0000	16993
Crashes with damage	0.9535	0.2106	0.0000	1.0000	17116
Severity					
Fatalities	0.0010	0.0315	0.0000	1.0000	17116
Incapacitating	0.0045	0.0728	0.0000	3.0000	17116
Evident injury	0.0511	0.2465	0.0000	4.0000	17116
Possible injury	0.2952	0.6138	0.0000	11.0000	17116
Intersection/Traffic characteristics					
Speed estimate	20.0807	15.7065	0.0000	100.0000	16986
Log(daily volume)	10.4050	0.4323	8.8209	11.1452	17110
Average amber time	4.1236	0.2216	3.0000	5.0500	17110
Driver condition/characteristics					
Apparently normal	0.5566	0.4968	0.0000	1.0000	17110
Ill	0.3200	0.4665	0.0000	1.0000	17110
Impaired	0.0163	0.1267	0.0000	1.0000	17110
Medical condition	0.2180	0.1460	0.0000	1.0000	17110
Asleep	0.0416	0.1997	0.0000	1.0000	17110
Female	0.4722	0.4992	0.0000	1.0000	17110
Type of vehicle collision					
Rear end slow/stopped	0.3398	0.4737	0.0000	1.0000	17116
Left turn same	0.0983	0.2978	0.0000	1.0000	17116
Left-turn different	0.0315	0.1748	0.0000	1.0000	17116
Sideswipe same direc.	0.0601	0.2377	0.0000	1.0000	17116
Sideswipe opp. direc.	0.0091	0.0950	0.0000	1.0000	17116
Fixed object	0.0072	0.0845	0.0000	1.0000	17116
Head-on	0.0151	0.1219	0.0000	1.0000	17116
Rear turning	0.0123	0.1101	0.0000	1.0000	17116
Ran off road right	0.0098	0.0983	0.0000	1.0000	17116
Right turn different	0.0075	0.0862	0.0000	1.0000	17116
Right turn same	0.0106	0.1026	0.0000	1.0000	17116
Backup	0.0097	0.0980	0.0000	1.0000	17116
Other vehicle colli.	0.0283	0.1659	0.0000	1.0000	17116
Vehicle characteristics					
Passenger car	0.6683	0.4709	0.0000	1.0000	17110
Pickup	0.0984	0.2979	0.0000	1.0000	17110
Van	0.0440	0.2050	0.0000	1.0000	17110
SUV	0.0968	0.2957	0.0000	1.0000	17110
Light truck	0.0303	0.1715	0.0000	1.0000	17110
Land use					
Residential	0.2127	0.4092	0.0000	1.0000	17116
Commercial	0.7537	0.4309	0.0000	1.0000	17110
Industrial	0.0048	0.0691	0.0000	1.0000	17116
Institutional	0.0191	0.13672	0.0000	1.0000	17110
Technology variables					
Shoulder/lap	0.8933	0.3088	0.0000	1.0000	17116
RLCPRES	0.1577	0.3645	0.0000	1.0000	17110
Airbag	0.6654	0.4719	0.0000	1.0000	17110
Deployed front	0.0721	0.2586	0.0000	1.0000	17110
Deployed side	0.0064	0.0799	0.0000	1.0000	17110
Others					
Under ride	0.0226	0.1487	0.0000	1.0000	17110
Over ride	0.0152	0.1225	0.0000	1.0000	17116
No visual obstruction	0.9210	0.2697	0.0000	1.0000	17110

Descriptive statistics

The descriptive statistics in Table 2 provide some information about the data. These statistics show that those involved in the crashes were mostly men (52.78%) and appeared normal (55.66%). However, a sizable percentage (21.80%) had medical conditions and 32.00% were ill. Those impaired by drugs and/or alcohol accounted for only 1.63% of the crashes and a driver falling asleep behind the wheel accounted for 4.16% of the crashes.

An observation from the table is that 75.37% of the crashes occurred where the predominant land use is commercial and 21.27% occurred where the predominant land use is residential. Very few crashes occurred near where the major land use is industrial or institutional. This distribution of where the crashes occurred could reflect prior determination by traffic engineers concerning where to locate traffic lights. Since commercial land uses generate a lot of vehicular traffic, it is common to locate traffic lights near them. The same can be said of residential land use, though to a lesser extent.

A further observation is that 95.35% of the crashes involved property damage costing $2,259.33 on the average, and 29.52% of the crashes involved possible injuries. The data also show that very few accidents were fatal (0.10%), incapacitating (0.45%), or involved evident injury (5.11%). In short, most of these crashes were minor. One reason for this may be the low average estimated traveling speed of 20.08 miles per hour for the vehicles in the crashes and 66.54% of these vehicles having airbags. Also, it may be because 89.33% of the vehicle occupants wore seatbelts. Furthermore, in 7.21% of the vehicles, the airbags in the front passenger compartment deployed possibly reducing injuries to the driver and front-seat occupants, while in 0.64% the side airbags deployed. This latter percentage could indicate the most severe crashes. In fact, since this percentage is very close to that for fatalities it is possible that both percentages show the same type of crash.

Due to the preponderance of passenger cars in traffic streams, we would expect that most of the crashes would involve passenger cars. Indeed, this is the case as the data reveals. The data shows that though various types of vehicles were involved in crashes, most (66.83%) were passenger cars, 9.84% were pickups, 9.68% were sports utility vehicles, 4.4% were vans, and 3.3% were light trucks. The rest, 5.8% included single unit trucks, tractor-trailers, taxicabs, motorcycles, and school buses, etc.

Because the focus of the study is on vehicular crashes, the data does not show crashes between vehicles and pedestrian, animals, bicyclists, or movable objects. For this reason, the percentages in the table for types of crashes do not sum to one hundred. The data show that 33.98% of the intersection crashes involved running into the back of a slowed or stopped vehicle, 9.83% involved vehicles making a left in the same roadway, 6.01% involved sideswiping a vehicle in the same direction, while 3.15% involved vehicles turning left on different roadways. Each of the other entries in the table shows a percentage that is less than three percent.

Correlations

The data was analyzed using various statistical methods including correlation to establish relationships among the independent variables. This is particularly important to identify linear dependencies among the variables that could seriously affect the reliability of the estimated coefficients. Appendix A shows the correlations between the independent variables. Clearly, most of these correlations are very low suggesting that linear dependencies would not be a problem in using these variables in the equations to be estimated. However, close observation reveals a sizable positive correlation between red light cameras and traffic volume. Since higher traffic volumes are generally associated with minor accidents because speed tends to be low, we should expect some relationship between red light cameras and minor accidents. In the next section, we will examine if this relationship indeed exists when other confounding variables are accounted for. Interestingly, there is a negative correlation between female drivers and the reporting of an accident being related to falling asleep or a medical condition.

4. ANALYSIS OF CRASH-LEVEL SEVERITY

This section analyzes factors that can predict the most severe injury sustained by all involved in a crash. Milton and Mannering (1998) argue that since most accident frequency data are over-dispersed, the appropriate model to use is the negative binomial model. However, in this section we categorize individual accidents by severity and perform analysis to determine the factors that explain the severity category. For example, the occurrence of a fatal accident or an accident involving property damage is recorded as one and non-occurrence as a zero. Because these occurrences are the dependent variables in our equations, negative binomial models are inappropriate. Because the dependent variable is dichotomous, we use probit and logit equations to estimate an equation for each type of accident.

In addition, there are very few fatal crashes in the data; therefore, they are combined with those that result in incapacitating injuries and one equation estimated for them. In all, two equations are estimated for crash severity and they are: 1) a probit model for fatal and incapacitating crashes, and 2) a probit model for evident injury. These equations are of the form,

$$Y = X\beta \tag{1}$$

Where Y is the dependent variable, X is a subset of the independent variables in Table 2 and β is a vector of the coefficients to be estimated. These independent variables are the characteristics of signalized intersections, traffic and road characteristics, land use characteristics, driver characteristics, technology, and environmental variables.

Results

Fatal and incapacitating injuries

Table 3 shows the maximum likelihood estimates of the coefficients of the equation for the combined fatal and incapacitating injuries from vehicle crashes. The fit statistics show that the model fits the data relatively well. At the 0.5 threshold level (i.e., predict that fatalities and incapacitating injuries equal to one if the fitted probability of these injuries occurring is greater than 0.5), 99.67% of the actual ones and zeroes in the dependent variable are correctly predicted. However, it is worth noting that with this threshold, the model correctly predicts the zeroes better than it predicts the ones. For example, while it correctly predicts 99.565% of the zeroes, it incorrectly predicts 98.61% of the ones. These results show that the data is quite unbalanced with many zeroes. In fact, our data has 72 crashes involving fatal or incapacitating injuries (i.e., probability = 0.0055) coded as ones compared to 16,263 crashes coded as zeroes that did not result in these injuries. These levels of prediction notwithstanding, the results provide useful information to explain crashes that result in fatal and incapacitating injuries.

The effect of technology variables on fatal and incapacitating injuries: From the coefficients in Table 3, some information can be gleaned about the effect of technology variables on crashes that result in fatalities and incapacitating injuries. These technology variables are the presence of airbags in the vehicles involved in the crashes, front airbag deployed, and side airbag deployed. We observe that the coefficient of the presence of airbags in vehicles is negative and statistically significant at the 0.0019 level. This result confirms the commonly accepted notion that airbags reduce fatalities and incapacitating injuries. On the other hand, when we examine the coefficients of airbag deployment, the opposite results are obtained. Here, the coefficients of both the front and side airbags deploying are positive and statistically significant at the 0.0000 and 0.0371 levels respectively. These positive coefficients suggest that when the front and side airbags deploy in crashes, they could result in incapacitating injuries and possibly fatalities.

The relative contributions of the technology variables to incapacitating injuries and fatalities from intersection crashes are obtained by examining their marginal effects. These marginal effects are presented below. Clearly, they show that the marginal effect of the side airbag deploying versus not deploying is not statistically significant. On the other hand, the marginal effects of the front airbag deploying and there being an airbag in a vehicle involved in a crash at an intersection are statistically significant. The sizes of these marginal effects show that when a front airbag deploys it may increase the probability of injuries and fatalities occurring more than the reduction in this probability when there is an airbag in a vehicle.

Table 3: Binomial Probit: Fatality and Incapacitating Injuries

Weighting variable	**None**
Number of observations	16335
Iterations completed	10
Log likelihood function	-363.1880
Restricted log likelihood	-462.3978
Chi squared	198.4197
Degrees of freedom	11
Prob[ChiSqd > value] =	.0000000

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	-4.6425	0.7427	-6.251	0.0000	
Occupants	-0.1114	0.0798	-1.396	0.1627	1.3895
Amber time (seconds)	0.4233	0.1756	2.410	0.0160	4.1235
Speed estimate	-0.0027	0.0003	-10.659	0.0000	14.9971
(Speed estimate)^2	0.0003	0.0000	7.183	0.0000	630.1699
Apparently normal	0.2033	0.1027	1.979	0.0479	0.5573
Rear-end slow/stopped	-0.3460	0.1310	-2.641	0.0083	0.3508
Head-on collision	0.6055	0.2071	2.924	0.0035	0.0140
Passenger car	0.1848	0.1146	1.613	0.1068	0.6683
Airbag	-0.3443	0.1110	-3.103	0.0019	0.6664
Airbag deployed front	0.5935	0.1386	4.282	0.0000	0.0618
Airbag deployed side	0.6917	0.3317	2.085	0.0371	0.0053

```
 Fit Measures for Binomial Choice Model
 Probit   model for variable FTL
 Proportions P0= .9956   P1= .0044
 N =   16335 N0=   16263   N1=      72
 LogL =  -363.18796 LogL0 =  -462.3978
 Estrella = 1-(L/L0)^(-2L0/n) = 0.0136
     Efron   McFadden    Ben./Lerman
    .05280     .21456         .99173
    Cramer  Veall/Zim.      Rsqrd_ML
    .05830     .22398         .01207
 Information  Akaike I.C. Schwarz I.C.
 Criteria          .04594     842.78870
Frequencies of actual & predicted outcomes
Predicted outcome has maximum probability.
Threshold value for predicting Y=1 = .5000
            Predicted
Actual      0    1  |  Total
  0     16263    0  |  16263
  1        71    1  |     72
Total   16334    1  |  16335
Analysis of Binary Choice Model Predictions Based on Threshold =  .5000
Prediction Success
Sensitivity = actual 1s correctly predicted                      1.389%
Specificity = actual 0s correctly predicted                    100.000%
Positive predictive value = predicted 1s that were actual 1s 100.000%
Negative predictive value = predicted 0s that were actual 0s  99.565%
Correct prediction = actual 1s and 0s correctly predicted     99.565%
Prediction Failure
False pos. for true neg. = actual 0s predicted as 1s            .000%
False neg. for true pos. = actual 1s predicted as 0s          98.611%
False pos. for predicted pos. = predicted 1s actual 0s          .000%
False neg. for predicted neg. = predicted 0s actual 1s          .435%
False predictions = actual 1s and 0s incorrectly predicted      .435%
```

	Mean	Standard. Error	t-value	Probability
Airbag present in vehicle	-0.0022	0.0008	-2.631	0.0085
Front airbag deployed	0.0071	0.0030	2.409	0.0160
Side airbag deployed	0.0105	0.0104	1.015	0.3103

Types of accidents vs. fatal and incapacitating injuries: Types of accidents also have significant effects on fatalities and incapacitating injuries. Two types of crashes are examined here. They are running into the back of a slowed or stopped vehicle, and head-on collision. Both types of crashes have opposite and statistically significant effects on fatal and incapacitating injuries. Running into the back of a slowed or stopped vehicle at an intersection is negatively associated with suffering incapacitating injuries and fatalities, showing that these crashes are generally not serious. On the other hand, a head-on collision is a very serious crash and it is positively associated with fatalities and incapacitating injuries. Examining the marginal effects of these types of crashes, we observe that when an intersection crash involves running into the back of a slowed or stopped vehicle, its marginal effect on the probability of fatality and incapacitating injuries occurring is negative (-0.0016) and statistically significant (0.0034). Contrariwise, when the crash involves a head-on collision, its marginal effect (0.0080) is not statistically significant (0.1304).

Driver condition vs. fatal and incapacitating injuries: Driver condition at the time of a crash also affects fatality and incapacitating injuries. We noted this in the data section; here we consider it explicitly in modeling fatal and incapacitating injuries. While the data provides a variety of information about driver condition, only one is considered in Table 3 and this is if the driver involved in the crash appeared normal. The log-likelihood estimation did not converge to a solution when other descriptors of driver condition were included in the model. The results of the estimation in Table 3 show that those involved in crashes that involved fatalities and incapacitating injuries appeared normal. The estimated coefficient of this driver condition and its associated probability are respectively 0.2033 and 0.0479. And, its marginal effect of 0.0011 with a level of significance of 0.0464 shows that apparently normal drivers contribute very little (less than 1%) to the probability of a crash occurring that leads to fatalities and incapacitating injuries. This suggests that such crashes may be due to drivers who do not appear normal or who may have some medical problems.

Intersection and traffic characteristics vs. fatal and incapacitating injuries: Four variables are used to capture the effects of intersection and traffic characteristics on crashes that result in fatalities and injuries. They are the type of vehicle involved in the crash (represented by passenger car), the estimated speed of the vehicle in the crash, the square of this estimated speed, and amber time setting. The results show that the coefficient of passenger car, though positive, is not statistically significant. Its probability of 0.1068 is outside the commonly acceptable range, i.e., $p < 0.10$. Thus, we cannot say that when passenger cars are involved in crashes at signalized intersections they would be associated with more fatalities and incapacitating injuries than other vehicles. When also we examine the amber time settings at signalized intersection, it can be said that they appear to be associated with high levels of crashes that result in fatalities and incapacitating injuries. Here, we observe that the coefficient of amber time is 0.4233 with a probability of 0.0160, which is statistically significant. However, the marginal effect of amber time is 0.0022 (probability = 0.0185) and shows that increasing it by one second would increase by 0.22% the probability of a crash occurring that involves fatalities and incapacitating injuries.

The effect of estimated travel speed on crashes involving fatalities and incapacitating injuries is examined with two variables, one linear and the other quadratic. The results show that both variables have coefficients that are opposite in signs and that are highly significant (probability < 0.0000). While the linear speed term has a negative coefficient, the quadratic term has a positive coefficient. These coefficients imply that as estimated travel speed increases there would be an initial reduction in crashes resulting in fatalities and incapacitating injuries. This could occur if it increases traffic flow and reduces stop-and-go operations. However, at some point an increase in speed would increase the probability of crashes resulting in fatalities and incapacitating injuries.

Evident injury

Table 4 shows the maximum likelihood estimate of crashes that involved evident injury. Here, we removed from the data all crashes that involved fatal, incapacitating, and possible injuries. Similar to those crashes that involved fatal and incapacitating injuries, the model fits the data very well. The Chi-squared of the model is 1193.714 and its probability is

0.0000. We also observe that at the 5% threshold level the model predicts 99.87% of the actual zeroes and 9.233% of the actual ones, which reflects the unbalanced nature of the data. Specifically, the data contains 4.92% of crashes that resulted in evident injuries. Combined, at this threshold level, the model correctly predicts 95.411% of the actual ones and zeroes.

The effect of technology variables on evident injury: The technology variables considered in this equation include the presence of red light cameras at intersections, drivers' use of shoulder and lap belts, and use of only lap belt at the time of the crash. Others are the presence of an airbag in a vehicle involved in a crash, front airbag deployed, and side airbags deployed. Obviousl,y from the table the presence of a red light camera at an intersection is not related to crashes that result in evident injuries. This is quite surprising since red light cameras are touted for reducing crashes at intersections, particularly severe crashes that cause injuries. However, it is consistent with what Burkey and Obeng (2004) found in their study of red light cameras using a subset of data included in this study.

The relationship between the presence of airbags in vehicles and evident injury is negative and statistically significant and similar to what we found between crashes that result in fatal and incapacitating injuries and airbags. The coefficient of the presence of an airbag in a vehicle is -0.3932 and it is significant at the 0.0000 level. Therefore, the probability of crashes occurring at signalized intersections that result in evident injuries could reduce if the vehicles had airbags. However, when the airbags deploy they do not have the same negative effect on evident injuries as the presence of an airbag in a vehicle. Whether the airbag deploys in front or on the side, its effect is to increase the probability of an evident injury occurring. This is quite clear from the coefficients of 1.5974 (probability = 0.0000) and 1.3766 (probability = 0.0000) for side and front airbags deploying respectively. The marginal effects of the presence of an airbag in a vehicle, and front and side airbags deploying also are statistically significant and are shown below. These marginal effects show that when either the front or the side airbag deploys the probability of evident injury occurring is far larger than the decrease in the probability of an evident injury occurring in a vehicle that has an airbag.

Table 4 – Binomial Probit Model of Evident Injury

Log likelihood function	**-1950.749**
Restricted log likelihood	-2547.606
Chi squared	1193.714
Prob[ChiSqd > value] =	.0000000

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X|
Constant	-0.5411	0.5854	-0.924	0.3554	
Red light camera	0.0492	0.0685	0.718	0.4727	0.1568
Log(daily traffic volume)	-0.0985	0.0561	-1.755	0.0793	10.4067
No visual obstruction	0.4742	0.0939	5.052	0.0000	0.9098
Rear-end slow/stopped	-0.5898	0.5922	-9.960	0.0000	0.3354
Head-on collision	0.2887	0.1368	2.110	0.0348	0.0133
Side swipe same direction	-0.6681	0.1251	-5.343	0.0000	0.0738
Backup	-1.3336	0.6535	-2.041	0.0413	0.0119
Passenger car	0.0653	0.0551	1.185	0.2362	0.6414
Pickup	0.1051	0.0808	1.300	0.1937	0.1076
Straight truck	-0.7676	0.4301	-1.785	0.0743	0.0112
Shoulder/lap belt	-0.6925	0.0680	-10.190	0.0000	0.8883
Shoulder belt only	-0.6686	0.1681	-3.977	0.0001	0.0193
Airbag deployed side	1.5974	0.1799	8.879	0.0000	0.0042
Airbag deployed front	1.3766	0.0656	20.991	0.0000	0.0473
Airbag	-0.3921	0.0479	-8.186	0.0000	0.6604
Occupants	0.0640	0.0203	3.155	0.0016	1.3218
Speed estimate	-0.0033	0.0003	-11.845	0.0000	15.8964
$(\text{Speed estimate})^2$	0.0002	0.0000	7.438	0.0000	629.4370
Under ride	0.2889	0.1369	2.110	0.0349	0.0225
Residential land use	0.0834	0.0520	1.604	0.1088	0.2087

Fit Measures for Binomial Choice Model

Proportions P0= .950801 P1= 0.0492

N = 12988 N0= 12349 N1= 639

LogL = -1950.74869 LogL0 = -2547.6057

Estrella = 1-(L/L0)^(-2L0/n) = .09942

Efron	McFadden	Ben./Lerman
0.1749	0.2343	0.9229

Cramer	Veall/Zim.	Rsqrd_ML
0.1754	0.2987	0.0878

Information	Akaike I.C.	Schwarz I.C.
Criteria	0.3036	4100.4048

Threshold value for predicting Y=1 = .5000

	Predicted		
Actual	0	1	Total
0	12333	16	12349
1	580	59	639
Total	12913	75	12988

Analysis of Binary Choice Model Predictions Based on Threshold = .5000

Prediction Success	
Sensitivity = actual 1s correctly predicted	9.233%
Specificity = actual 0s correctly predicted	99.870%
Positive predictive value = predicted 1s that were actual 1s	78.667%
Negative predictive value = predicted 0s that were actual 0s	95.508%
Correct prediction = actual 1s and 0s correctly predicted	95.411%
Prediction Failure	
False pos. for true neg. = actual 0s predicted as 1s	.130%
False neg. for true pos. = actual 1s predicted as 0s	90.767%
False pos. for predicted pos. = predicted 1s actual 0s	21.333%
False neg. for predicted neg. = predicted 0s actual 1s	4.492%
False predictions = actual 1s and 0s incorrectly predicted	4.589%

	MARGINAL EFFECT	STD. ERR	T-VALUE	PROB.
Shoulder and lap	-0.0695	0.0102	-6.844	0.0000
Shoulder belt only	-0.0217	0.0027	-8.147	0.0000
Airbag deployed front	0.2392	0.0198	12.096	0.0000
Airbag deployed side	0.3339	0.0667	5.010	0.0000
Airbag	-0.0027	0.0037	-7.251	0.0000

Two other technology variables whose relationships with evident injury we examined are shoulder and lap belts. When used together, these belts have negative relationships with there being evident injuries in crashes at intersections. The coefficient of using lap and shoulder belts together is -0.6925 with a probability of 0.0000. Similarly, when shoulder belts are used alone they reduce the probability of evident injuries occurring in crashes at signalized intersections. The coefficient of using shoulder belts alone is -0.6686 with a probability of 0.0001. Although these coefficients are very close, their marginal effects in the above table show that the injury reduction effect of using shoulder and lap belts together is more than three times the effect of using a shoulder belt alone. To be exact, when shoulder and lap belts are used the probability of sustaining evident injury in a crash reduces by 6.95% (probability = 0.0000), compared to a reduction of 2.17% (probability = 0.0000) in sustaining evident injury in an accident at an intersection.

Combining these results we consider a typical automobile user, a driver wearing a combined shoulder and lap belt and driving a vehicle equipped with front and side airbags that deploy during a crash at a signalized intersection. The marginal effects of the technology variables show that such a typical automobile driver would have a 50.09% chance of sustaining an evident injury. If the same driver used only the shoulder belt, the probability of him/her sustaining evident injury becomes 54.87%. If the vehicle did not have a side airbag the probability of an evident injury occurring would reduce to 16.70%.

Types of accidents vs. evident injuries: Evident injuries may also be due to the types of crashes that occur. Though our data contain many types of crashes, we focus only on those for which we obtained statistically significant coefficients. Three types of accidents qualified to be included in the model of evident injury and two had negative and statistically significant coefficients. These two are crashing into the back of a slowed or stopped vehicle and backing up, and their respective coefficients are -0.6681 (0.0000) and –1.3336 (0.0413), where the probabilities are in parentheses. Thus, the probability of a crash at a signalized intersection resulting in evident injury is smaller when it involves running into the back of a slowed or stopped vehicle, or when the crash results from a vehicle backing up. These results are also borne out when we examine the marginal effects of these types of crashes. Such an examination leads to the table below, which shows that the reduction in the probability of evident injury is larger than occurs from side swiping a vehicle that is moving in the same direction.

	MARGINAL EFFECT	STD. ERR	T-VALUE	PROB.
Back of slowed/stopped vehicle	-0.0302	0.0027	-11.356	0.0000
Head on collision	0.0225	0.0136	1.660	0.0969
Side swipe vehicle in same direction	-0.0235	0.0024	-9.651	0.0000

While both types of crashes are negatively related to evident injury, Table 4 and above table show that head on collisions are positively associated with sustaining an injury. The coefficient of head on collision is 0.2887 and it is significant at the probability level of 0.0348. However, the probability of the marginal effect of head on collision is very weak, leading us to surmise that there is not strong evidence to suggest that head on crashes at signalized intersections are not strongly related to evident injury. This may be because these types of crashes seldom occur particularly in an environment where raised medians are used at signalized intersections to separate traffic flowing in opposite directions.

Type of vehicle versus evident injury: To examine the impact of the type of vehicle involved in a crash on evident injury we included three types of vehicles in the model. They are passenger cars, pickups, and straight trucks. Both passenger cars and pickups have positive coefficients in the model, but these coefficients are not statistically significant. This shows that we cannot be confident that evident injury would be observed when these two types of vehicles are involved in crashes. Contrary to these results we find that the coefficient of a straight truck is -0.7676 and its level of significance of 0.0743 is very weak, just as is its marginal effect. Specifically, the marginal effect of a straight truck is 0.0068 with a level of significance of 0.2288. Together these results show that type of vehicle does not have a statistically significant effect on crashes at a signalized intersection that result in evident injuries.

Traffic volume and speed vs. evident injury: Table 4 also shows the effects of traffic volume and speed on the probability of evident injuries occurring in crashes at signalized intersections. The coefficient of traffic volume is –0.0985 with a significance level of 0.0793, which shows that its relationship with evident injuries is very weak. However, when we examine the effect of estimated speed the vehicle was traveling when the accident occurred, its linear and quadratic terms are highly statistically significant. The coefficient of the linear and quadratic terms are –0.0033 (0.0000) and 0.0002 (0.0000) respectively, where the terms in parentheses are the probabilities. As we have argued in previous discussions, the negative coefficient of the linear term shows that the probability of evident injury occurring is low when estimated speed is high, while the coefficient of the quadratic term shows that beyond some point an increase in estimated speed would be associated with an increase in the probability of evident injury occurring.

Type of land use and evident injury: The effect of land use on evident injury is also in Table 4. Here, the considered land use is residential and it is found that it does not have a statistically significant effect on evident injury. Though its coefficient is positive, its level of significance of 0.1088 shows this coefficient is not different from a zero. Thus, crashes involving evident injury are found everywhere and not confined to specific places or where some predominant land uses occur.

Other factors vs. evident injury: Besides the above results, crashes that involve under rides result in evident injury. The coefficient of this variable is 0.2889 and its level of significance is 0.0349. Similarly, when a crash is a result of no visual obstruction it results in evident injuries. The coefficient of no visual obstruction is 0.4742 with a probability of 0.0000. It follows that crashes at intersections that result in evident injuries cannot be attributed to visual obstructions.

5. DETERMINANTS OF INJURIES IN TWO-VEHICLE CRASHES

The discussions in the previous section were concerned with fatalities and incapacitating injuries, and evident injuries. In those discussions, we considered all types of crashes and did not distinguish between single car and multiple car crashes. In this section, we consider the most common type of crashes at signalized intersections, crashes involving two vehicles. To do so we pulled all crashes that involved only two vehicles and classified them in terms of severity using the KABCO method. The fatalities and severe injuries (Type A) occurred so rarely in the data set that they were combined with evident injuries and non-disabling injuries (Type B) into a category called ‘Severe.” Possible injuries (Type C) were examined for comparison. This process yielded 6,188 events with 12,376 vehicles involved containing 17,922 occupants. The proportions of persons who had severe and possible injuries are 4.9% and 29.4% respectively. Of the types of accidents recorded, 39.4% involved angle crashes, 14.8% left-turning vehicles, 1.6% head-on collisions, 32.9% rear-ending a slow or stopped vehicle and 2.0% right-turning vehicles. About 54% of the crashes involved male drivers, 98% of the drivers wore seatbelts during the crash, and 1.9% of the drivers were impaired. For 8.1% of the crashes, air bags deployed, and 5% involved visibility obstruction. Table 5 presents descriptive statistics for the explanatory variables in the study of two vehicle crashes. Using this data we analyzed the factors that influence the number of severe (K, A, B) and possible (C) injuries that occur in two-vehicle crashes. These factors include the characteristics of the vehicle containing the occupants who suffered injuries as well as the characteristics of the other vehicle involved in the crash. Of key interest here are the estimated speeds of both vehicles at impact and the types of vehicles involved.

To focus on the most common occurrences with a relatively simple model, we restricted attention to accidents involving cars, pickups, SUVs, minivans, and “single unit trucks.” These single unit trucks include many types of delivery trucks that have two axles. Examining all of the possible combinations of these vehicle types would require 20 different pairings to be examined. To reduce this to 12 categories, pickups and minivans were combined into one category because of their similar weights.

The model

Again, recall that the number of injuries of each type is a count variable. So, we employ Poisson regression models to analyze two-vehicle crashes. However, it would be improper to ignore the fact that the number of severe injuries and the number of minor injuries occurring in the same vehicle are related. A method that considers this relationship is therefore needed. Some authors have used Seemingly Unrelated Regression (SUR) type model tailored for count data in analyzing this relationship (King, 1989; Winkelmann, 2000). A relatively new approach is the bivariate Poisson constructed using a trivariate-reduction technique, which we use in this section.

Table 5: Descriptive Statistics of Data for Two-Vehicle Crashes

Description	Variable	Mean	Std. Dev.
Number of Occupants	ocpnt	1.448	0.841
Damage estimate	dmgest	2251.449	2006.815
Speed at impact	spatimp	15.705	12.722
Categorical Variables:		Proportion	
Severe injuries	severe	0.049	
Possible (C)-injuries	cinj	0.294	
Road surface condition (wet)	wet3	0.200	
Angle crash type	angle	0.394	
Left turning crash type	leftturn	0.148	
Headon collision	headon	0.016	
Rear end crash type	rear	0.329	
Right turning crash type	rturn	0.020	
Gender	male	0.540	
Seatbelt use	seatbelt	0.982	
Airbag deployment	airbag	0.081	
Visibility obstruction	visob	0.049	
Impairment	impair	0.019	
Proportion of number of cars involved	car	0.703	
Number of pickups involved	pickup	0.107	
Number of SUVs involved	suv	0.101	
Number of light-trucks involved	ligtrk	0.032	
Number of trucks involved	truck	0.057	
Under ride	uride	0.022	

To understand this technique let X_1, X_2, and X_3 be independent Poisson random variables. We can construct conceptual models in the standard (log-link) way, modeling the expected values of the X_i as $\lambda_i = e^{X_i B_i}, i \in \{1,2,3\}$. Then, both $\{X = X_1 + X_3, Y = X_1 + X_3\}$ follow a bivariate Poisson distribution. The joint probability density function of this distribution is

$$P(X = x, Y = y) = \exp(-(\lambda_1 + \lambda_2 + \lambda_3)) \frac{\lambda_1^x}{x!} \frac{\lambda_2^y}{y!} \sum_{k=0}^{\min(x,y)} \binom{x}{k} \binom{y}{k} k! \left(\frac{\lambda_3}{\lambda_1 \lambda_2} \right)^k$$

This formulation is convenient because it explicitly allows for a relationship between X and Y, namely, cov $(X, Y) = \lambda_3$. If this covariance is zero, the estimation reduces to the product of two independent Poisson distributions (called a *double Poisson* model by Johnson et al.

(1997)). It has been shown that a misspecification of a binomial Poisson as a double Poisson model will cause the model's parameters to be overestimated (Karlis & Ntzoufras, 2003).

Application of this equation requires estimating three equations jointly, i.e., two "independent" equations for severe (fatal and incapacitating injuries) and evident injuries, and a covariance equation showing the interrelatedness of these two equations.[3] The two "independent" equations explaining severe and possible injuries in the first vehicle in a two-vehicle crash use three types of explanatory variables. First, is a set of indicator variables to account for the types of vehicles in two-vehicle accident. There were twelve possible accident types (e.g., the first vehicle is a car and the second vehicle is SUV), and we created interaction variables for them and used a car-car accident as the reference category, therefore omitting it from the estimation. These interaction variables measure the relative impact of a collision in comparison to riding in a car and being in an accident where the other vehicle is also a car. For reference, there were 3,090 car-car accidents (7,180 vehicles) involving 304 severe injuries and 1,941 C injuries for the 8,914 occupants of the vehicles. This implies mean risk rates of 0.0341 and 0.2177 per occupant. The coefficients of the interaction variables should be understood in relation to these values. The third equation, which constructs the covariance between the two types of injury severity, contains the estimated speed of both vehicles at impact and the natural logarithm of the number of occupants is used as the exposure variable.

Diagnostics and Goodness of Fit

The most common problem facing Poisson models is over-dispersion. Since the Poisson is a single parameter distribution, such that the mean is equal to the variance, one must check for a violation of this assumption. Over-dispersion is particularly problematic because if the variance is much larger than the mean type one errors can result because of underestimated standard errors. In the two-vehicle crashes, the means and variances are very close for each of the two dependent variables. From our data, the mean of the severe injuries is 0.049, and the variance of the residuals is 0.056. For the possible injuries variable the mean is 0.294, and the variance of the residuals is 0.355. These small amounts of over-dispersion will not affect the results in this paper because the bivariate Poisson's standard errors are estimated via a bootstrap method. The standard errors reported here were generated with 200

[3] The estimates were derived using the *bivpois* package for ***R*** developed by D. Karlis and I. Ntzoufras. See http://stat-athens.aueb.gr/~jbn/current.htm for more information.

estimations of the model parameters using randomly generated observations as the dependent variables.

We report several standard measures of goodness of fit as described in Greene (2002, p. 742). They include the pseudo R^2, which is based on deviances (Cameron & Windmeijer, 1997) and compares the amount of improvement of the model over a null model compared to that of a saturated model. Another common pseudo R^2 measure is the *likelihood ratio index*, sometimes called the McFadden R^2. This index is less appropriate for working with discrete data, because the maximum possible value of R^2_{lri} is considerably less than zero (Cameron & Trivedi, 1998). We also report the Akaike and Bayesian (Schwartz) Information Criteria (BIC) for the model as well as for the null and saturated models for comparison. These latter measures become lower as the model improves, but contain a penalty for loss of degrees of freedom. There is little evidence that one is superior to the other; however, the BIC has a bias toward a simpler model.

Results

Table 6 shows the results of crashes involving two vehicles. The R^2_{DEV} is 0.4416 and it suggests a reasonable fit of the model to the data. The first section of the results estimates the interactive effect of different types of vehicles being involved in a crash. Again, the omitted (reference) category for these interaction variables is car*ocar, which would describe the risk of injury when riding in a passenger car involved in a crash with another car. A positive coefficient would suggest a higher expected number of injuries and negative lower. For severe injuries, a car hit by a pickup or minivan, SUV, or truck has positive estimated coefficients. However, all *t*-statistics for these interactions are slightly too low for a confident conclusion of higher risk of injury in these accidents. We find statistically significantly more dangerous interactions between pickups and minivans, and riding in an SUV and being hit by (or hitting) a pickup or minivan.

For possible injuries, we find a statistically significant increase in risk for a car in an accident with a truck. However, we find significant decreases for passengers of pickups or minivans in an accident with a car, and for SUV passengers in an accident with either a car or another SUV. There is borderline statistical significance for the decrease of possible injuries for SUV passengers in an accident with a pickup/minivan. Deployment of an airbag is statistically significant and positive for both severity levels. This result may reflect injuries caused by airbags, but likely reflect the force and location of impact. If the driver of a vehicle is impaired, its occupants are less likely to have possible injuries, but much more likely to have severe injuries.

If the driver is male, there is no effect on severe injuries, but a significant decrease in possible injuries. This could reflect the well-known aversion of males to seek medical attention unless there is an obvious need (Hemmila, 2004). A driver's use of a seat belt is very strongly related to a decrease in severe injuries, but not possible injuries. Being in a vehicle that under rode another vehicle, i.e., goes under another vehicle in a crash, is less likely to involve possible injuries and more likely to involve severe injuries (the latter with unconvincing levels of statistical significance).

The final category of explanatory variables is accident type. The estimates are all positive and most are statistically significant. The reference category (omitted) for these dummy variables is all types of crashes other than those listed. A large component of these crashes is sideswipe, which rarely causes injuries. Therefore, the accident types listed are the more dangerous types of accidents.

The covariance equation relating the possible and severe injuries contains the speed of both vehicles and controls for the number of occupants. Of course, as the number of occupants increases the number of injuries also increases. We are unaware of any previous research that has empirically investigated the impact of the speeds of each vehicle on the number of injuries. Consistent with expectations, the speed of both vehicles matters, but the speed of the vehicle you are traveling in has a larger impact than the speed of the other vehicle.

Table 6: Two-Vehicle Accidents

Equation 1: Severe Injuries				Equation 2: Possible Injuries			
Variable	Coeff.	SE	t ratio	Variable	Coeff.	SE	t ratio
(Intercept)	-3.139	0.342	-9.184	(Intercept)	-1.691	0.154	-10.976
car*opickmini	0.207	0.152	1.367	car*opickmini	0.073	0.059	1.237
car*osuv	0.264	0.171	1.544	car*osuv	0.079	0.057	1.381
car*otruck	0.317	0.219	1.452	car*otruck	0.244	0.080	3.030
pickmini*ocar	0.039	0.167	0.234	pickmini*ocar	-0.353	0.066	-5.324
pickmini*opickmini	0.524	0.267	1.965	pickmini*opickmini	0.033	0.126	0.266
pickmini*osuv	0.368	0.427	0.860	pickmini*osuv	-0.306	0.177	-1.728
pickmini*otruck	0.266	1.841	0.145	pickmini*otruck	-0.031	0.240	-0.131
suv*ocar	0.032	0.203	0.157	suv*ocar	-0.339	0.079	-4.273
suv*opickmini	0.824	0.274	3.010	suv*opickmini	-0.272	0.170	-1.600
suv*osuv	-0.093	1.008	-0.092	suv*osuv	-0.390	0.164	-2.375
suv*otruck	-0.873	5.293	-0.165	suv*otruck	-0.253	0.294	-0.861
airbag	1.646	0.087	18.828	airbag	0.742	0.046	16.247
impair	0.672	0.211	3.180	impair	-0.381	0.149	-2.554
male	-0.036	0.085	-0.428	male	-0.387	0.035	-11.153
seatbelt	-1.524	0.161	-9.460	seatbelt	-0.111	0.128	-0.867
uride58	0.413	0.271	1.523	uride58	-0.396	0.121	-3.281
angle	1.430	0.313	4.576	angle	0.772	0.088	8.768
headon	1.890	0.353	5.346	headon	0.988	0.134	7.373
Leftturn	1.212	0.320	3.791	leftturn	0.706	0.094	7.488
Rear	0.187	0.335	0.558	rear	0.789	0.093	8.511
rturn	1.240	0.419	2.958	rturn	0.045	0.189	0.237
Equation 3: Common Factors							
Variable	Coeff.	SE	t ratio				
(Intercept)	-10.252	0.893	-11.482				
spatimp	0.070	0.016	4.388				
spother	0.033	0.013	2.481				
logocc	3.255	0.448	7.273				
BIC Saturated Null Model 257705.07 22428.97 21450.32				$R^2_{DEV} = 0.4416$			
AIC Saturated Null Model 56801.46 22404.62 21060.72				$R^2_{lri} = 0.0640$			

6. LAND USE AND VISIBILITY EFFECTS ON ACCIDENT RATES

The previous section did not consider the effects of land use and visual obstruction on crashes. We did so in Section 4 and did not find statistically significant relationships between severity of crashes and land use. This, of course, does not mean that crashes are unrelated to land use. For, as we have argued, entrances to commercial areas tend to generate a lot of traffic and increase the risk of a crash occurring. We take this issue again in this section because very little research has focused specifically on the relationship of visibility and land use characteristics to accident rates. Ward and Wilde (1996) evaluate the effect of improving visibility at railway crossings, finding evidence of risk-compensating behavior, and no demonstrable effect on safety. Ossenbruggen, Pendharker, and Ivan (2001) study the relationship between various types of land use (e.g., residential, shopping, and commercial) and accidents, finding that shopping areas may have low accident rates if they are more pedestrian-friendly. In the present study, however, we use total crashes instead of different types of crashes and include in the analysis the degree of visibility obstructions and the type of predominant land use at each intersection that may contribute to accident rates.

In their reports of accidents, police officers can select between six choices to describe the predominant land use at an intersection and these are listed in Table 7[4]. Different officers sometimes report different choices, especially at intersections with mixed uses. Therefore, we construct land use variables by calculating the percentage of accident reports that describe an area as residential, commercial, and so on. In this way, an intersection is not restricted to be in only one category, but the percentages are likely to reflect the mixed land uses at that intersection[5]. Similarly, we use the accident data to construct a variable to describe the degree to which visibility obstructions play a role in causing accidents. We calculate the proportion of all accidents at an intersection in which a vision obstruction played a role. From Table 7 we included trees, crops, brushes, building(s), embankment, sign(s), hillcrest, and blinded by sunlight and other lights. The observed percentages range from a zero percent to 16.7 percent of accidents at each intersection being related to a visibility obstruction.

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[4] Although “UNKOWN” is a valid option on the accident report, there were no accidents in this dataset where the Development Type was “unknown”.

[5] Initially, zoning maps were to be used for determining land use. However, city officials correctly pointed out that current zoning may not accurately reflect the current land use, especially in cases where undeveloped property exists. Additionally, many intersections have two or more land uses represented.

Table 7: Land Use and Visibility Variables

Development Types:	**Vision Obstruction Types:**
Farms, woods, pastures	None
Residential	Vehicle window(s) obscured
Commercial	Trees, crops, brush, etc.
Institutional	Building(s)
Industrial	Embankment
Unknown	Sign(s)
	Hillcrest
	Parked vehicle(s)
	Vehicle(s) in traffic/moving
	Blinded, headlights
	Blinded by sunlight
	Blinded, other lights
	Other

The models run are the same as in Burkey and Obeng (2004), with the variables above added and their results are in Table 8. As can be seen, the coefficient of visibility is not statistically significant. This could be due to the lack of a truly objective measurement of visibility. The land use variables are comparative to the reference category, which is residential land use. The only statistically significant category is for a commercial area, which has an estimated coefficient of 0.3716. This coefficient shows that accident rates in commercial areas are approximately 45% higher than elsewhere, *ceteris paribus*. This is consistent with the fact that commercial areas are activity centers, and have many vehicles entering and exiting their driveways, thereby creating the potential for traffic conflict and accidents. Additionally, many activities in such areas may distract drivers and cause them to have accidents.

Table 8: Poisson Regression Model of Total Crashes

Number of observations					**17157**
Log likelihood function					-17128.05
Restricted log likelihood					-19025.40
Chi squared					3794.704
Degrees of freedom					22
Prob[ChiSqd > value]					
Chi- squared					20000.05772
RsqP					0.1879
G - squared					18354.87585
RsqD					0.1715
Variable	Coefficient	Std.Err.	b/St.Er.	P[Z>z]	Mean(X)
Constant	-11.4690	0.3561	-32.203	0.0000	
MONTH	-0.0004	0.0000	-5.340	0.0000	29
RLCPRES	0.3729	0.0046	8.139	0.0000	0.0029
TOTLTL	0.0063	0.0016	3.977	0.0001	1.6445
DEDRTL	0.0027	0.0023	1.158	0.2470	0.4419
SWLK	0.1198	0.0028	4.271	0.0000	0.4319
SLDMED	-0.0075	0.0030	-2.465	0.0137	0.1761
PEDSIG	-0.2235	0.0032	-6.993	0.0000	0.2591
NLT	0.0016	0.0036	0.460	0.6457	0.1030
NTR	0.1487	0.0026	5.698	0.0000	0.2093
SNOW	-0.0021	0.0008	-2.597	0.0094	0.4123
PRECIP	0.0008	0.0005	1.683	0.0923	3.6540
TOTLN	-0.0002	0.0005	-0.417	0.6764	8.1395
ST1FLOW	-0.0036	0.0025	-1.441	0.1497	0.9103
ST2FLOW	-0.0036	0.0025	-1.441	0.1497	0.8605
ST1RED	0.0021	0.0013	1.630	0.1030	1.5402
ST2RED	0.0021	0.0013	1.630	0.1030	1.5437
AMBD1	-0.1179	0.0029	-4.059	0.0000	0.5701
AMBD2	-0.1179	0.0029	-4.059	0.0000	0.5685
ST1SP	-0.0007	0.0002	-2.809	0.0050	34.635
ST2SP	-0.0007	0.0002	-2.809	0.0050	34.8339
LNEWADV	1.0995	0.0033	33.136	0.0000	10.1392
VISOB	-0.0002	0.0005	-0.382	0.7024	1.1265
FARM	-0.1506	0.3895	-0.387	0.6990	0.0011
COMM	0.3716	0.0041	8.969	0.0000	0.64854
INST	-0.2040	0.1591	-1.282	0.1999	0.0029
INDUST	0.2389	0.461459	0.518	0.6047	0.0006

7. DETERMINANTS OF PROPERTY DAMAGE COSTS

Although we have analyzed crash severity and the impacts of land use and vision obstruction on crashes, we still have not considered property damage costs. These costs form a substantial portion of crash costs, and for this reason, we examine these costs in this section.

Property damage costs do not follow the same distribution as crash severity data. As we have noted, the property damage cost data is censored and continuous over strictly positive values. It follows that this cost cannot be negative. With this type of distribution, the appropriate model to estimate is a left-censored Tobit model. The underlying regression in the Tobit model is,

$$Y = Y^{*} = \beta X + \varepsilon, \qquad if \;\; L < Y^{*} < U, \qquad where \;\; \varepsilon \sim N\left[0,\sigma^{2}\right] \qquad (1)$$

Where Y^{*} is a latent variable, U and L are the thresholds, and $Y^{*} \geq L$ shows lower-tail censoring. Additionally, $Y^{*} \leq L$ shows upper-tail censoring. Woodridge (2000) shows that, based upon equation (2), the log-likelihood function for each observation *(i)* is of the form,

$$\ell_{i}(\beta,\sigma) = 1(Y_{i} = 0)log[1-\Phi(X_{i}\beta/\sigma)] + 1(Y_{i} > 0)log\{(1/\sigma)\phi[(Y_{i} - X_{i}\beta)/\sigma]\} \qquad (2)$$

This equation is summed over all observations and then maximized to obtain the coefficients of the Tobit equation. Furthermore, he shows that when the dependent variable follows a Tobit model, the expectation of this variable is a nonlinear function of the independent variables and the estimated coefficients. This characteristic of the Tobit model shows that its estimated coefficients cannot be interpreted as the marginal effects of the independent variables on the observed dependent variable even though the relationship is linear in equation (2). The marginal effect of each *j* variable must be calculated so that we can make informed judgments about the contribution of each variable to property damage cost and total crash cost. This marginal effect of each variable *(j)* when censoring occurs on the left is

$$\frac{\partial E\left[y|X\right]}{\partial X_{j}} = \beta_{j}\Phi\left(X\beta/\sigma\right) \qquad (3)$$

Property damage cost model

Vehicles that are involved in accidents at signalized intersections sustain damages that depend upon the characteristics of the intersection, driver, type of accident, types of vehicles involved in the accident, technology features in the vehicle, and predominant land-use. A model of damage cost was estimated in this study. The dependent variable in this model is the damage cost estimate in the accident reports. Intersection characteristics are the presence of red light cameras, the logarithm of the sum of traffic volumes on all the roads at an intersection, and amber time on the major road. The characteristics and condition of drivers are in terms of gender (female = 1, male = 0), illness suspected (ILL35), medical condition (MEDCON35), impairment (IMPAIR35), apparently normal (APPN35), and falling asleep (ASLEEP35). Besides these variables, the damage cost model includes the following: hitting the rear of a slowed vehicle (RSLO10), a fixed object (FIXOBJ10), rear of a turning vehicle (RTRN10), side-swiping a vehicle moving in the opposite direction (SSOPD10), side swiping a vehicle moving in the same direction (SSSDXN10), involvement in a head-on collision (HEADON10), and hitting a vehicle backing up (BACKUP10). We also distinguish between the following types of vehicles: passenger cars (PCAR41), pickups (PICKUP41), vans (VAN41), sports-utility vehicles (SUV41), and light trucks (LIGTRK41). The technology variables in the model are the presence of red light cameras at an intersection (RLCPRES), presence of airbags in the vehicles (AIRBAG), front airbag deployed (DEPFRT28), and side airbags deployed (DEPBS28), while the land use variables are commercial (COMMERC2) and institutional (INSTITU2). Other variables are estimated speed of vehicle (SPDEST), its quadratic term (ST2), and a variable showing if the crash involved a vehicle riding under another vehicle (URIDE58). Except traffic volume, amber time, and the speed, all other variables are binary.

Table 9 shows the results of estimating a censored Tobit regression equation for property damage cost and the fit measures. Obviously, from this table, most of the coefficients are statistically significant at commonly accepted levels, i.e., $p < 0.10$. The only variable whose coefficient is statistically insignificant is gender, i.e., being a female driver. The marginal effects of the variables are in Table 10 and are the changes in property damage cost resulting from changes in the continuous variables, or from having the binary variables take values of one instead of zero. These marginal effects measure the unit worth or cost of the variables.

Technology variables vs. property damage cost: Examining the technology variables, the results in Table 10 can be broken into two areas. First, we observe that the introduction of a red light camera at an intersection has a very weak marginal effect on property damage cost. It appears that the presence of a red light camera reduces the property damage cost of a crash by only $66.70. This result, significant at the 0.0912 level, shows that our data do not support a strong association between red light cameras and the property damage costs of a crash. However, this negative effect suggests that it is a benefit of installing a red light camera.

Second, we find that the presence of airbags and airbags deploying increase property damage costs of crashes. The amounts of these cost increases are $51.42, $1,897.67, and $2,211.94 for having an airbag in a vehicle, front airbag deploying, and both side airbags deploying respectively. Thus, property damage cost is higher when the side airbags deploy than when the front airbag deploys. It follows that if the airbag in a vehicle does not deploy in a crash the presence of an airbag would add only a miniscule $51.42 to the vehicle damage cost, which is not highly significant statistically. This reflects the fact that the force of the impact is so low as to result in only minor property damage. However, if the front and side airbags deploy, the force of the impact would be so high as to cause property damage in excess of $4,000.

Type of vehicle vs. property damage cost: Property damage costs are generally expected to be high when large vehicles are involved in crashes with small vehicles. This is because large vehicles cause a lot of damage to small vehicles when both are involved in a crash. We also expect that when large vehicles are involved in crashes at signalized intersections they would sustain less property damage than small vehicles. This commonly held expectation is borne out by the marginal effects in Table 10. Here, we find that vans, pickup trucks, light trucks, sports utility vehicles, and passenger cars sustain increasing levels of property damage when they are involved in crashes. Specifically, the amounts of property damage sustained by these vehicles are $799.35, $844.47, $949.31, $1,016.37, and $1,084.35 respectively. Using these results, we find that when pickup trucks, light trucks, sports utility vehicles and passenger cars are involved in crashes, the property damage costs are 5.64%, 18.76%, 27.15%, and 35.65% larger than the corresponding costs when vans are involved in crashes.

Table 9: Property Damage Costs

Dependent variable	DMGEST
Weighting variable	None
Number of observations	17110
Iterations completed	6
Log likelihood function	-147490.7
Threshold values for the model:	
Lower= .0000 Upper=+infinity	
LM test [df] for Tobit= 4513.110[31]	
ANOVA based fit measure = .146836	
DECOMP based fit measure = .161542	

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X|
Constant	-436.9799	478.0596	-.914	0.3607	
RLCPRES	-77.2453	45.7272	-1.689	0.0912	0.1577
LNEWADV	-84.7541	41.1753	-2.058	0.0396	0.4050
ST1AMB	336.3575	71.5452	4.701	0.0000	4.1236
APPN35	946.2601	109.1617	8.668	0.0000	0.5566
ILL35	850.5339	110.9104	7.669	0.0000	0.3200
IMPAIR35	700.4164	160.2978	4.369	0.0000	0.0163
MEDCON35	792.9404	149.5237	5.303	0.0000	0.0218
ASLEEP35	807.0585	132.7353	6.080	0.0000	0.0416
VOB34	196.7931	68.5288	2.872	0.0041	0.9210
RSLO10	-959.4279	34.8375	-27.540	0.0000	0.3398
FIXOBJ10	857.7788	181.8743	4.716	0.0000	0.0072
RTRN10	-784.9244	139.3939	-5.631	0.0000	0.0123
SSOPD10	-400.2542	161.5606	-2.477	0.0132	0.0091
HEADON10	396.9033	125.0108	3.175	0.0015	0.0151
SSSDXN10	-1000.2132	65.8989	-15.178	0.0000	0.0601
BACKUP10	-1206.8901	157.8349	-7.647	0.0000	0.0097
FEMALE	-22.0447	32.4147	-.680	0.4965	0.4722
PCAR41	1255.7010	77.6419	16.173	0.0000	0.6683
PICKUP41	977.91862	88.7067	11.024	0.0000	0.0984
VAN41	925.66589	103.9312	8.907	0.0000	0.0440
SUV41	1176.9875	89.9666	13.082	0.0000	0.0968
LIGTRK41	1099.3224	114.7870	9.577	0.0000	0.0303
SPDEST	3.5395	0.4782	7.402	0.0000	12.6951
ST2	0.2857	0.0256	11.162	0.0000	637.9631
URIDE58	697.6382	103.0574	6.769	0.0000	0.0226
COMMERC2	-137.5802	37.9727	-3.623	0.0003	0.7537
INSTITU2	-267.6135	116.3823	-2.299	0.0215	0.0191
AIRBAG	59.5504	33.8400	1.760	0.0784	0.6654
DEPFRT28	2197.5488	61.2456	35.881	0.0000	0.0721
DEPBS28	2561.4902	189.8623	13.491	0.0000	0.0064
	Disturbance standard deviation				
Sigma	1971.113491	10.9732	179.630	.0000	

Table 10: Marginal Effects

They are computed at the means of the Xs.					
Scale Factor for Marginal Effects .8635					
Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Constant	-377.3487	412.7823	-0.914	0.3606	
RLCPRES	-66.70439	39.4873	-1.689	0.0912	0.1577
LNEWADV	-73.1884	35.5570	-2.058	0.0396	10.4050
ST1AMB	290.4574	61.7833	4.701	0.0000	4.1236
APPN35	817.1315	94.2149	8.673	0.0000	0.5566
ILL35	734.4683	95.7294	7.672	0.0000	0.3201
IMPAIR35	604.8361	138.3954	4.370	0.0000	0.0163
MEDCON35	684.7341	129.0857	5.304	0.0000	0.0218
ASLEEP35	696.9256	114.5860	6.082	0.0000	0.0416
VOB34	169.9383	59.1754	2.872	0.0041	0.9210
RSLO10	-828.5024	30.1451	-27.484	0.0000	0.3398
FIXOBJ10	740.7245	157.0583	4.716	0.0000	0.0072
RTRN10	-677.8120	120.3829	-5.630	0.0000	0.0123
SSOPD10	-345.6347	139.5162	-2.477	0.0132	0.0091
HEADON10	342.7410	107.9551	3.175	0.0015	0.0151
SSSDXN10	-863.7220	56.9454	-15.168	0.0000	0.0601
BACKUP10	-1042.1953	136.3185	-7.645	0.0000	0.0097
FEMALE	-19.0364	27.9912	-0.680	0.4964	0.4722
PCAR41	1084.3455	66.9958	16.185	0.0000	0.6683
PICKUP41	844.4698	76.5624	11.030	0.0000	0.0842
VAN41	799.3476	89.7132	8.910	0.0000	0.0395
SUV41	1016.3734	77.6461	13.090	0.0000	0.0679
LIGTRK41	949.3066	99.0890	9.580	0.0000	0.0033
SPDEST	3.0565	0.4118	7.422	0.0000	12.6951
ST2	0.2467	0.0222	11.139	0.0000	637.9631
URIDE58	602.4370	89.0062	6.768	0.0000	0.0262
COMMERC2	-118.8058	32.7912	-3.623	0.0003	0.7537
INSTITU2	-231.0944	100.5007	-2.299	0.0215	0.0191
AIRBAG	51.4241	29.2227	1.760	0.0785	0.6654
DEPFRT28	1897.6670	53.1141	35.728	0.0000	0.0721
DEPBS28	2211.9439	164.0544	13.483	0.0000	0.0064
Sigma	0.0000	.... (Fixed Parameter)........			
Note: E+nn or E-nn means multiply by 10 to + or -nn power.)					

Type of crash vs. property damage cost: Table 10 also shows the effects of various types of crashes on property damage costs. In particular, it shows that the property damage costs of some crashes are lower than the comparable costs of other crashes. The crashes that seem to result in low property damage costs are side swiping a vehicle moving in the opposite direction (-$345.63), hitting the rear of a turning vehicle (-$677.81), hitting the rear of a slowed vehicle (-$828.50), side swiping a vehicle moving in the same direction (-$863.72), and crashing into a vehicle backing up (-$1,042.20). The dollar amounts in parentheses are how much less the property damage costs are compared to all other crashes. For example, the cost of a crash occurring at a signalized intersection that involves a vehicle backing up is $1,042.20 less than the property damage costs of all accidents that occur in other situations. Examining the amounts, we observe that the cost reductions are large in absolute terms for the less occurring crashes.

Three types of crashes whose property damage costs are larger than all other comparable crashes are head-on collisions, running into a fixed object, and a crash that involves a vehicle going under another vehicle. A vehicle that is involved in head-on collisions sustains $342.72 more in property damages compared to a vehicle that is involved in other accidents. Similarly, a vehicle that crashes into a fixed object at a signalized intersection sustains property damage costs of $740.72 compared to vehicles in different crashes. In addition, when a crash involves one vehicle going under another vehicle, the property damage cost is $602.44. Because these costs are positive, these crashes are the ones to reduce. Actions to reduce crashing into a fixed object, for example, could include widening the shoulder and placing road signs and lamp posts safe distances away from the road.

Intersection characteristics vs. property damage costs: We have argued earlier that intersection characteristics such as traffic volume and amber time setting could have effects on property damage costs from crashes. In Table 10, we find that the marginal effects of these characteristics are statistically significant and generally positive. They show that lengthening the amber time by one second, for example, could increase property damage cost of a crash by $290.46. This finding seems contrary to previous studies, which suggest that lengthening the amber time would reduce crashes. If the results of these other studies were valid, the costs of crashes would also decrease. While our results show that crash costs increase with longer amber time, they also show that higher traffic volumes at an intersection are associated with smaller amounts of crash costs. From Table 10, a percentage increase in traffic volume would reduce the property damage costs of a crash by $73.19. This reduction occurs because at higher traffic volumes speed reduces, stop-and-go operations increase, and the crashes that occur are minor. Often, these crashes are running into the back of a slowed vehicle, which, as our previous discussion shows, is associated with low crash costs.

Driver characteristics and condition vs. crash costs: In both Tables 9 and 10, the effects of driver characteristics and condition on crash costs are also shown. We find that gender does not have a statistically significant relationship with crash costs. Therefore, we cannot say that female drivers are involved in more costly crashes than male drivers are involved. However, the condition of the driver at the time of the crash does have appreciable effect on property damage cost. Here, we find that being impaired by alcohol or drugs increases property damage cost from a crash by $604.84, compared to increases of $684.73, $696.93, and $734.47 from having a medical condition, falling asleep, and falling ill respectively. This is quite surprising since we had expected that impaired drivers would be more involved in crashes that involved large property damage costs. That we did not find that to be the case must be qualified. Our data deals with city roads with lower speed limits and not rural roads where speed limits are high and where very severe accidents and high property damage costs have been reported for impaired drivers. Another surprising result in Table 10 is that drivers who appear normal tend to be involved in crashes that result in a large property damage cost. This cost is $817.13.

Land uses vs. property damage cost: The environment where a crash occurs could also have some effects on property damage costs. In heavily built areas with large traffic generators, we expect more crashes to occur because of a large number of turning vehicles. For example, this would be the case of large shopping centers such as malls. Even here, our earlier results still suggest that because of increases in traffic volume, speed would be low and fewer minor crashes could be observed. Alternatively, our earlier results seem to point to the fact that such places would observe less severe crashes compared to other areas in the city because they would have more turning vehicles and increased traffic volume. These earlier results are supported by what we found by analyzing the costs of crashes that occur where the predominant land uses are commercial or industrial. Crashes that occur where the predominant land use is commercial involve property damage costs that are $118.81 less than from crashes that occur near other land uses indicating that these are minor accidents. Similarly, we found that a crash occurring where the predominant land use is institutional results in property damage cost that is $231.09 less than those that occur elsewhere. Thus, both commercial and institutional land uses are associated with lower property damage costs from crashes.

Other factors vs. property damage cost: Other factors that contribute to property damage costs and that we examined in Tables 9 and 10 are those relating to the environment and driver behavior. Regarding environmental variables, Table 10 shows that when a crash is a result of a visual obstruction it adds $169.94 to property damage cost. Using the estimated speed of vehicle and its quadratic term to proxy driver behavior, we find that the coefficients of both variables are highly significant statistically, showing that they contribute to high property damage costs from crashes. Yet, their effects on property damage costs are very small, showing that they do not increase these costs appreciably.

8. CONCLUSIONS

The purpose of this research is to extend the previous work of Burkey and Obeng (2004) by expanding the data over a longer time series, and including technological, visibility, vehicle, traffic, land use and demographic variables to investigate the determinants of accident rates, accident severity and property damage cost. To accomplish this purpose the research estimates models to explain accident rates, accident severity (including two-vehicle crashes), and property damage cost for accidents that occur at signalized intersections.

Severity and type of accident

Fatalities and incapacitating injuries: For accidents that involve fatalities and incapacitating injuries, the results are that while airbags reduce fatalities, incapacitating injuries and fatalities are high when the front airbags deploy. The marginal effects of side airbags deploying are not statistically significant in such accidents. Other factors that tend to increase fatalities and incapacitating injuries are type of accident (head on collision), higher amber time, and speed. With regard to speed, its initial effect reduces fatalities and incapacitating injuries, perhaps reflecting road quality, though ultimately it increases them. For example, among the roads studied, those with higher posted speed limits have solid medians over most of their lengths, multiple lanes, and good signage. On the other hand, fatalities and incapacitating injuries are low when the accident involves running into the back of a slowed or stopped vehicle, which shows these types of accidents are minor. In fact, these are the types of accidents that most often do not require a police accident report to be completed because of low property damage costs, unless the occupants sustain some injuries.

Evident injury: Compared to fatalities and incapacitating injuries, evident injury reduces in accidents in which the occupants wear shoulder belts only, shoulder and lap belts, and where the vehicles involved have airbags. These findings are not new and echo what has been shown to be the case by several researchers. They may also show effectiveness of regulations regarding seatbelt use, as well as reflect vehicle age and quality of vehicles. For example, all new vehicles have front airbags and seatbelts, and they are built to higher standards of quality than old vehicles. Similar to what we observed earlier, evident injuries increase when airbags deploy in such accidents thus giving support to the advice often given to drivers not to sit close to airbags. These injuries also increase when the accident involves head on collision. However, they initially are decreasing with speed, but increase at higher speeds. We also found that evident injuries are low in accidents that involve running into the back of a slowed or stopped vehicle and side swiping a vehicle moving in the opposite direction, and are high in accidents that involve head-on collisions.

Two-vehicle accidents: Some of the above findings apply to two vehicle accidents as well. For example, we found that possible injuries increase in two vehicle accidents when airbags deploy. Additionally, we found increased risk of possible injury in car-truck accidents, and decreased risk of possible injury in pickup (minivan)-car, SUV-car, and SUV-SUV accidents. Being a male driver is also associated with reduced risk of possible injury in a two-vehicle accident, and possible injuries occur in all types of accidents.

For two vehicle accidents that result in severe injuries, we did not obtain as many statistically significant results as we obtained for possible injuries. Here, we did not find statistically significant effects of most two-vehicle accidents on increased risk of severe injuries except accidents between pickups (or mini buses), and between SUVs and pickups. This risk of injury increases when various types of accidents occur (except running into the back of a slowed or stopped vehicle), when airbags deploy and a driver is impaired, and it reduces when vehicle occupants use seat belts.

Property damage costs

Besides type and severity of accidents our analysis of property damage costs show that intersections with red light cameras are associated with low property damage costs in accidents but that this cost is not very strong statistically. On the contrary, vehicles with airbags sustain more damage costs in accidents than those without airbags but the amount of this increase is not very high. However, when the front airbag in a vehicle deploys or when both the front and side airbags deploy in accidents they result in large property damage costs. For example, when both the front and side air bags deploy they result in a 16.56% ($314.27) increase in property damage cost over the cost of the front airbag alone deploying. This cost increase shows that the force of the collision is very high in accidents in which both the side and front bags deploy. Additionally, such accidents tend to be severe with vehicles sustaining frontal and side damages.

Another finding is that property damage cost is highest when passenger cars are involved in accidents followed in decreasing order by sports utility vehicles (perhaps due to their rollover effects), light trucks, pickups, and vans. Specifically, compared to a van, the property damage costs of pickup trucks, light trucks, sport utility vehicles, and passenger cars are higher by 5.64%, 18.76%, 27.15%, and 35.65% respectively. Therefore, among the vehicles analyzed, vans sustain the least damage cost in accidents at signalized intersections. Yet another finding is that the amount of property damage cost depends upon the type of accident. Everything else constant, accidents that involve running into the back of a slowed or a turning vehicle, and side swiping a vehicle moving in the same or a different direction are less costly than other accidents. The accidents whose property damage costs are very high are colliding into a fixed object, under ride, and head on collision.

We found that most driver characteristics affect property damage costs of accidents. Drivers who are categorized as apparently normal in police accident reports are those who cause very large property damage costs in accidents. They are followed respectively by those classified as having fallen ill, and those who fell asleep (or fainted or lost consciousness) while driving, had medical conditions, or were impaired by medications, drugs or alcohol. Driver errors or distractions may be the reason those who appear normal are involved in more costly accidents than others are. Although our results show low property damage costs from impaired drivers we caution that they do not show that impairment results in low property damage costs in every case. This is because we did not analyze blood alcohol levels, nor did we study rural highways where most severe drunk driving accidents have been observed. The fact that the roads analyzed are in urban areas, have more traffic, lower posted speed limits, and are better designed with clear sight distances than rural roads, may account for the rather low property damage costs when impaired drivers are involved in accidents at signalized intersections. Gender is the only driver characteristic that was not related to property damage cost in a statistically significant way. Thus, we cannot say that accidents involving female drivers tend to involve more property damage costs than those involving males.

Recommendations

Crash severity and property damage costs can be reduced by adopting some traffic countermeasures. From our results, it is appears that installing red light cameras at some intersections could reduce property damage costs of accidents somewhat (*given that an accident has already occurred*). Though we find this to be true, the effects of these cameras on reducing the frequency of accidents and accident severity are unsettled with some studies finding they increase accidents and others finding they reduce accidents. In this study, we did not find a statistically significant impact of red light camera on severity of crashes, but continue to find an increase in accident rates after the installation of a red light camera. Therefore, we should be careful where to install red light cameras. We also find that evidence in favor of speed reduction since we have found that speed increase ultimately increases injuries and property damage costs resulting from crashes.

Lastly, for traffic engineers and transportation planners, the marginal effects of the variables in the property damage cost model, particularly for the different vehicles, should be useful in estimating the benefits or costs of intersection improvements. For example, if the traffic composition and accident rates are known it should be possible to calculate the monetary benefits of accident reduction from traffic countermeasures.

REFERENCES

Acierno, S., Kaufman, R., Rivara, F. P., Grossman, D. C. and Mock, C. 2004. Vehicle mismatch: injury patterns and severity. *Accident Analysis & Prevention,* 36 : 761-772

Advocates for Highway and Auto Safety, 2001. “Intersection Safety Potential Federal Funding Sources For Safety Improvements,” April. www.saferoads.org.

Bedard, M., Guyatt, G. H., Stones, M. J. and Hirdes, J. 2002. The independent contribution of driver, crash, and vehicle characteristics to driver fatalities. *Accident Analysis and Prevention*, 34: 717-727.

Blincoe, L. J., Seay, A. G., Zaloshnja, E., Miller, T. R., Romano, E. O., Luchter, S., and Spicer, R. S. 2002. Economic impact of motor vehicle crashes 2000. US. Dept of Transportation, National Highway traffic Safety Administration, Washington, DC.

Burkey, M. and Obeng, K. 2004. A detailed investigation of crash risk reduction resulting from red light cameras in small urban areas. Urban Transit Institute, North Carolina A&T State University, and U.S. Department of Transportation, Washington DC.

Cameron, A. C., and Windmeijer, F. A. G. 1997. An R-squared measure of goodness of fit for some common nonlinear regression models. *Journal of Econometrics,* 77: 329-342.

Cameron, A. C. and Trivedi, P. K. 1998. *Regression Analysis of Count Data*, Econometric Society Monograph No.30, Cambridge University Press.

Cook, P., and Tauchen, G. 1994. The effect of minimum drinking age legislation on youthful auto fatalities, 1970-77. *Journal of Legal Studies*, 13(1): 169-190.

FHWA. “Motor Vehicle Accident Costs,” Technical Advisory T 7570.2, October 31, 1994.

Giles, M. 2003. The cost of road crashes: A comparison of methods and recent Australian estimates. *Journal of Transport Economics and Policy*, 37(1):95-110.

Greene, W. H. 2003. *Econometric Analysis*, 5e, Prentice Hall, Hew Jersey.

Hauer, E., NG, J. and Lovell, J. 1988. Methods for evaluating highway improvements. *Transportation Research Record*, 48-61.

Hemmila, Donna. 2004. Sex Appeal. *Nurse Week,* (January 14).

IIHS, 2001. “Education Alone Won’t Make Drivers Safer. It won’t reduce crashes,” IIHS Status Report vol. 36, no. 5.

Institute of Transportation Engineers 2003. Making intersections safer: A toolbox of engineering countermeasures to reduce red-light running. Washington, DC.

Johnson, N., Kotz, S. and Balakrishnan, N. (1997). *Discrete multivariate distributions*. Wiley - New York.

Karlis, D and I. Ntzoufras. 2003. Analysis of sports data using bivariate Poisson models. *The Statistician*, 52: 381-393.

Kay, J. L., Neudorff, L. G. and Wagner, F. A. 1980. Criteria for removing traffic signals. Federal Highway Administration report FHWA/RD-80/104. U.S. Department of Transportation, Washington, D.C.

Keeler, T. E. 1994. Highway Safety, Economic Behavior, and Driving Environment. The *American Economic Review*, 84(3): 684-693.

King G. 1989. A seemingly unrelated Poisson regression model. *Sociological Methods and Research*, 17: 235-255.

Kockelman, K. M. and Kweon, Y. 2001. Driver injury severity: An application of ordered Probit models. Working paper, accessed on 10/08/04 from http://www.ce.utexas.edu/prof/kockelman/

Kweon, Y. and Kockelman, K. M. 2003. Overall injury risk to different drivers: Combining exposure, frequency, and severity models. *Accident Analysis and Prevention,* 35(4): 313-321.

Kulmala, R., 1994. “Measuring the Safety Effects of Road Measures at Junctions,” *Accident Analysis and Prevention,* Vol. 26. No. 4.

Levine, E., Bedard, M., Molloy, D. W., Basilevsky, A. 1999. Determinants of driver fatality risk in front impact object collisions. *Mature Medicine Canada*, 2: 239-242.

McCarthy, P.S., 1994. “An empirical-analysis of the direct and indirect effects of relaxed interstate speed limits on highway safety,” *Journal of Urban Economics* 36, 353–364.

McFadden, John and Hugh W. McGee, 1999. “Synthesis and Evaluation of Red Light Running Automated Enforcement Programs in the United States,” USDOT Publication # FHWA-IF-00-004.

McGee, H. W. and Eccles, K. A. 2003. “The impact of red-light camera enforcement on crash experience,” ITE Journal, 73(3), 44-48.

Michener, R. and Tighe, C. 1992. A Poisson regression model of highway fatalities. *The American Economic Review*, 82(2): 452-456.

Milton, J. and Mannering, F. 1998. The relationship among highway geometries, traffic-related elements and motor-vehicle accident frequencies. *Transportation,* 25: 395-413.

Mohamedshah, Y. M., Chen, W., and Council, F. M. 2000. Association of selected intersection factors with red-light running crashes. Presented at the Institute of Transportation Engineers.

National Highway Traffic Safety Administration. 2000. The economic impact of motor vehicle crashes 2000. U.S. Department of Transportation, NHTSA, Washington, D.C.

Neudorf, L. G. 1978. relationship between the removal of traffic signals and intersection accidents. *Transportation Engineering*, 0: 16-20.

Newstead, Stuart V., Maxwell H. Cameron, and L. Mark W. Leggett, 2001. "The Crash Reduction Effectiveness of a Network-wide Traffic Police Deployment System," *Accident Analysis and Prevention* 33.

Ossenbruggen, P., Pendharkar, J. and Ivan, J. 2001. Roadway safety in rural and small urbanized areas. *Accident Analysis & Prevention*, 33: 485-498.

Peltzman, S. 1975. The effects of automobile safety regulation. *Journal of Political Economy*, 83(4): 677-725.

Persaud, B., Hauer, E., Retting, R., Vallurupalli, R. and Mucsi, K. 1997. Crash reductions related to traffic signal removal in Philadelphia. *Accident Analysis and Prevention*, 29(6): 803-810.

Poch, M., and Mannering, F. 1996. Negative binomial analysis of intersection accident frequencies. *Journal of Transportation Engineering*, 122(2): 105-113.

Skabardonis, Alexander, 2001. "ITS Benefits: The Case of Traffic Signal Control Systems," TRB Paper No. 01-3286.

Tarawneh, Tarek M., Virenda A. Singh, Patrick McCoy, and Mohammed S. Tarawneh, 2001. "Deterring Red Light Violations through Advertising and Enforcement," TRB Paper No. 01-2555.

Troy, S.A, 2001. Memorandum to Area and Division Traffic Engineers, NCDOT, Dec. 3. Found at www.doh.dot.state.nc.us/preconstruct/traffic/safety/crashcosts.pdf.

Wang, Y., Ieda, H. and Mannering, F. 2003. Estimating rear-end accident probabilities at signalized intersections: Occurrence-mechanism approach. *Journal of Transportation Engineering*, July/August, 377-384.

Ward, N. J. and Wilde, G. J. S. 1996. Driver approach behaviour at an unprotected railway crossing before and after enhancement of lateral sight distances: An experimental investigation of a risk perception and behavioural compensation hypothesis. *Safety Science* , 22: 63-75.

Winkelmann, R. 2000. Seemingly unrelated negative binomial regression. *Oxford Bulletin of Economics and Statistics*, 62(4): 553-560.

Wooldridge, J. M. 2000. *Introductory econometrics, a modern approach*. United States: Southwestern College Publishing.

Zeeger, C. V., H.F. Huang, J.R. Stewart, R. Pfefer, and J. Wang, 1998. “Effects of a Towaway Reporting Threshold on Crash Analysis Results,” *Transportation Research Record* 1635, Transportation Research Board.

Appendix A
Correlation Matrix

		1	2	3	3	4	5	6	7	8	9	10	11	13	14	15	16	17	18	19	20	21	22	23
1.	RLCPRES	1.00																						
2.	LNEWADV	.40	1.00																					
3.	ST1AMB	.18	.23	1.00																				
4.	APPN	.01	.06	.07	1.00																			
5.	ILL	-.01	-.06	-.06	-.78	1.00																		
6.	IMPAIR	.01	.00	.00	-.15	-.09	1.00																	
7.	MEDCON	.00	.01	-.01	-.17	-.10	-.02	1.00																
8.	ASLEEP	-.00	.00	-.01	-.24	-.14	-.03	-.03	1.00															
9.	NOVOB34	.02	.04	.03	.12	.07	.01	.02	.02	1.00														
10.	RSLO10	.12	.21	.10	.05	-.03	-.01	.00	-.02	.07	1.00													
11.	FIXOBJ	-.01	-.04	-.01	-.03	.01	-.00	.00	.01	-.04	-.06	1.00												
12.	RTRN	.01	.03	.02	-.00	-.00	.00	.00	-.01	.01	-.08	-.01	1.00											
13.	SSOPD	-.02	-.03	-.02	-.02	.01	.02	-.01	-.00	-.03	-.07	-.01	-.01	1.00										
14.	HEADON	-.01	-.04	.01	-.01	-.00	.02	.00	.03	.01	-.09	-.01	-.01	-.01	1.00									
15.	SSSDXN	-.00	.00	-.02	-.01	-.00	.01	-.00	.00	-.02	-.18	-.02	-.03	-.02	-.03	1.00								
16.	BACKUP	-.01	-.02	.01	.00	-.00	.01	-.01	.00	.00	-.07	-.01	-.01	-.01	-.01	-.03	1.00							
17.	FEMALE	.00	-.01	-.02	-.01	.01	-.01	-.05	-.11	-.11	.01	-.03	-.00	.00	-.02	-.00	-.01	1.00						
18.	PCAR	-.01	-.01	-.04	-.10	.15	.03	.02	-.00	.08	-.03	-.02	-.02	.00	-.01	-.03	-.02	.16	1.00					
19.	PICKUP	.00	.00	.03	.12	-.11	-.02	-.02	.01	.03	.02	-.01	.01	-.02	.01	-.00	.02	-.21	-.48	1.00				
20.	VAN	-.01	-.01	.00	.03	-.04	.01	-.00	.03	.01	-.01	-.01	.01	-.00	.01	.01	.02	-.03	-.31	-.07	1.00			
21.	SUV	.02	.02	.03	.06	-.04	-.01	-.00	-.02	.04	.05	.00	.00	-.00	-.00	-.02	-.00	.01	-.47	-.11	-.07	1.00		
22.	LIGTRK	.00	.02	-.00	.04	-.05	-.00	.00	.02	.02	.00	-.02	-.00	.01	-.01	.01	-.01	-.01	-.25	-.06	-.04	-.06	1.00	
23.	SPDEST	.00	-.03	.04	-.01	.03	.00	.01	.02	.09	-.12	.04	-.02	.00	.03	.03	-.09	-.06	.01	.01	-.00	-.01	.01	1.00