Effects of Distractions on Injury Severity in Police-Involved Crashes

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ABSTRACT

A police cruiser can have multiple devices integrated in the cab, such as a laptop, radio, as well as strobe and siren controls. Although distractions might be a concern for police drivers, the effects of distractions on police-involved crashes have not been empirically studied before. As a first step in addressing this research gap, this paper reports the results of an ordered logit model built to investigate the likelihood of severe injuries when a crash involves distracted police drivers. The model was built on a national crash database: U.S. General Estimates System (2003 to 2008). In general, cognitive distractions (defined as being lost in thought or looked but did not see) were found to decrease injury severity, whereas in-vehicle distractions (due to any in-vehicle source) increased injury severity. In particular, crashes which involved police drivers distracted by in-vehicle sources were found to be more severe than crashes which involved civilian drivers distracted by in-vehicle sources. In contrast, crashes which involved non-distracted police drivers were less severe than crashes which involved non-distracted civilian drivers. A similar effect was observed for cognitive distractions.

INTRODUCTION

Driver distraction has been defined as "the diminished attention of the driver to the driving task" (*1*). Performing non-driving-related tasks can divert driver's attention away from activities critical for safe driving (*2*). Driving performance, thus, can degrade, leading to an increased crash risk (*3*). Cell phones, navigational systems, and passengers are well known sources of driver distraction.

Several studies demonstrated the effects of different types of distracting activities on driving performance (*4-10*). For example, cell phones were found to be significantly associated with an increase in more severe injuries (*11*). In terms of driving performance, dialing a cell phone impairs a driver's ability to maintain speed control and lateral position on the road (*5, 8, 9*). Text messaging while driving is likely to be riskier than simply talking on a cell phone (*4*), and has been shown to interfere with longitudinal and lateral control of the vehicle (*6*).

In addition to interacting with in-vehicle technologies, drivers also engage in non-technology-related activities while driving, potentially more often than they interact with the technology. More drivers involved in crashes are distracted by eating or drinking than by talking on a cell phone (*7, 10*). Presence of passengers in a crash increases the likelihood of more severe injuries (*12, 13*). Driver's attention might also diminish in the absence of non-driving-related activities, e.g., being lost in thought (*7*). Some studies, including this study, treat inattention in the absence of non-driving-related activities as a distraction category (*14*), whereas others distinguish inattention from distraction (*15*). Regardless of categorization, inattention in the absence of non-driving-related activities is a potential problem for traffic safety and needs to be studied.

Crash injury severity has been widely studied for civilian drivers. For example, (*13*) adopted an ordered probit model and (*16*) utilized a Bayesian ordered probit model to predict injury severity for various factors, such as driver's age, gender, alcohol use, and vehicle type. However, the associations between driver distraction and injury severity have not been widely studied. To our knowledge, only one injury severity study has focused on different types of driver distraction, but it was limited to teenage drivers (*12*). Thus, further research is needed to understand the effects of different distraction types on injury severity given various driver demographics.

Police officers constitute a demographic that is of particular interest. A police cruiser can have multiple devices integrated in the cab, such as a laptop, radio, as well as strobe and siren controls. Distractions caused by these devices have been raised as a potential concern (*17*). It should be noted that the existence of these devices in police cruisers may not necessarily translate to a high levels of distraction given different levels of training as well as policies and procedures for use of such technology. To our knowledge there is no previous research, which examined whether these technologies are indeed distracting to police officers and whether they affect injury severity. A simulator study of an in-vehicle environment similar to police cruiser cabs revealed that keyboard and display use decrease driving performance significantly (*18*). However, the participants in (*18*) were civilian drivers examined in a simulated environment and are not representative of police officers driving in the real world.

As a first step in addressing the research gaps identified above, our paper aims to assess the associations between driver distraction (in particular, in vehicle and cognitive distractions) and injury severity when a distracted police is involved in a crash. This goal is achieved with an examination of injury severities observed in distraction related crashes. The focus is on assessing how distractions relate to injury severity when the distracted driver is a police officer in comparison to when the distracted driver is a civilian. A U.S. national crash database, defined in the next section, is used as the basis of our analyses.

METHODS

Data Source

The U.S. DOT – General Estimates System (GES) crash data (*19*) from 2003 to 2008 were used in this study. The GES dataset is a stratified weighted sample of crashes, representing national crash trends, and includes information on several aspects of a crash such as driver demographics, crash type, type and presence of distractions, and injury severity. GES classifies injury severity on an ordinal scale with levels of no or possible injuries, non-incapacitating, incapacitating, and fatal injuries. The crash data were collected retrospectively; therefore exposure information (e.g., the amount of time spent performing distracting activities) is unavailable. As a result, the current study cannot assess crash risk. This study rather focuses on the crash outcome, in particular injury severity, given that a crash has already occurred. GES identifies the driver that is distracted, however it does not provide information on which driver is at fault or the root cause of a crash. Thus, the results of this study should also not be viewed as claiming causation. We assess associations between distractions and injury severity. As a first step in understanding the effects of distractions on police-involved crashes, we chose to focus on only two-vehicle crashes, for which the first harmful event is the direct collision of two moving vehicles. Both civilian and police-involved crashes are included in our analysis for comparison purposes. Crashes which involved a police officer in pursuit were excluded from our analysis.

Distraction Type Classification

Distraction categories used in GES, such as “cell phone” and “in-vehicle devices”, do not match with the special driving environment in a police cruiser. For instance, police use of radio communications may fit into the “cell phone” category better than the category of “in-vehicle devices”. Therefore, all in-vehicle secondary tasks which may compromise driver’s performance (i.e., cell phone, passengers, in-vehicle controls, eating, drinking, and smoking) are categorized as in-vehicle distractions in this paper. The cognitive distraction category includes “looked but did not see” and “being lost in thought” as specified in the GES data. This category has the same definition as inattention which is used in another study (*15*). A “no distraction” category, for which the driver was reported as not distracted, was also included.

In order to detangle the effects of different distraction types, we excluded crashes where both drivers were identified to be distracted. For example, if one driver is cognitively distracted and the other one is distracted by an in-vehicle source, then it is impossible to separate the effects of cognitive and in-vehicle distractions on the injury severities observed in this particular crash. To have even more control on potential confounds, for all driver (civilian, police) and distraction type (in-vehicle, cognitive, none) combinations we used cases for which the other driver was a non-distracted civilian.

Model Covariates

The model was built using an observation for each occupant (driver and passenger) involved in the crash. The response variable is the injury severity for that occupant. The observation for each occupant was also accompanied by information on both of the drivers (police vs. civilian, age, gender, type of distraction, etc.). Thus, the characteristics of both drivers were used as covariates for each occupant. Other covariates included in our model account for environmental conditions, crash profile, and occupant information.

Poor lighting conditions have been shown to increase crash risk (*20*). Lighting was therefore included as a variable with two categories: daylight vs. non daylight. Previous research revealed that location influences injury severity (*21*). Thus, urban/rural and highway/non-highway variables were included in the model. Given that weather and road surface conditions are closely related, only weather (good vs. bad) was included. Road alignment (curvy vs. straight) and relation to junctions (intersection vs. non intersection) were also included.

Three variables describing the crash profile were used: alcohol use, speeding, and crash type. These three variables were previously shown to influence injury severity (*12*, *13*). In our dataset, angular (46%) and rear-end (39%) crashes constitute the majority of all crash types, and the rest of the four crash types (sideswipe passing, sideswipe meeting, backed into, and head on) constitute less than 15%. Thus, in our model we included three types of crashes: angular, rear-end, and other. Common age thresholds used in driving safety and injury assessment are 25 and 65 (*22*, *23*). We adopted these thresholds for categorizing both drivers' and passengers' age. Occupants' (including drivers) age was defined to have three levels: 16 to 24 years old, 25 to 64 years old, and 65 years old and up. Gender and seating position (front or back) of the occupant were also included in the model. Seatbelt use was another variable used in our model, as it has been shown to be a significant factor in injury severity (*13*).

The majority of previous injury severity studies account for the characteristics of only the driver of the vehicle which the occupant belongs to (*12, 13*). Given that the at-fault driver is not identified in GES, it is important to account for the characteristics of the other vehicle's driver. Thus, driver demographics were incorporated in our model as combinations of two drivers' profiles. Drivers' gender had three levels: one male and one female, both male, or both female drivers. A combination of drivers' age was also included. As discussed above, the age groupings were based on commonly used thresholds: young (16 to 24), middle age (25 to 64), and old (65 and up) (*24*, *25*).

Data Analysis

An ordered logit model was built using the GENMOD procedure in SAS (Statistical Analysis System) version 9.2. Based on the GES data, injury severity is classified on an ordinal scale with levels of no or possible injuries, non-incapacitating, incapacitating, and fatal injuries. This model predicts the odds of severe injuries given that a crash has occurred. Therefore, the results should not be interpreted as crash risk or the odds of being involved in a crash with a certain level of injury severity.

An ordered logit model provides a strategy that takes into account the ordinal nature of data (*26*) and is represented with a set of equations as:

$$\ln\left[\frac{p_1}{1-p_1}\right]=\beta_{01}+\boldsymbol{\beta}\mathbf{X} \quad (1)$$

$$\ln\left[\frac{p_1+p_2}{1-p_1-p_2}\right]=\beta_{02}+\boldsymbol{\beta}\mathbf{X} \quad (2)$$

$$\ln\left[\frac{p_1+p_2+p_3}{1-p_1-p_2-p_3}\right]=\beta_{03}+\boldsymbol{\beta}\mathbf{X} \quad (3)$$

where p_1 represents the probability of a fatal injury, p_2 represents an incapacitating injury, p_3 represents a non-incapacitating injury. Thus, the equations represent the log-odds of severe injuries for: "fatal" versus "incapacitating", "non-incapacitating", and "no injuries" (eqn. 1); "fatal" and "incapacitating" versus "non-incapacitating" and "no injuries" (eqn. 2); "fatal", "incapacitating", and "non-incapacitating" versus "no injuries" (eqn. 3). β_{0i} represents the intercept and $\boldsymbol{\beta}$ is the matrix of coefficient estimates for predictor variables, $\mathbf{X}$.

A general issue with statistical models built on crash data is the incorrect assumption of independent observations. In theory, there are dependencies in crash data, as there can be multiple injuries within a vehicle and multiple vehicles involved in a crash. An ordered logit model is theoretically not appropriate for dependent data. In practice, logit models give approximate results that are very close to theoretically correct models such as general estimating equations (GEE) and multilevel logistic models, which themselves face many assumption issues when applied to crash data (*27*). Thus, we chose to use an ordered logit model with the assumption of independence. However, we partially incorporated the dependencies in our data by controlling for the driver characteristics of both vehicles. As previously mentioned, each occupant observation included information on both of the drivers.

RESULTS

After eliminating indirect crashes and crashes involving a police cruiser in pursuit, the dataset used in this study contains detailed information on a total of 17,485,261 (weighted) occupants (drivers and passengers) who were involved in two-vehicle crashes. Approximately 0.3% of the total 6,489,968 (weighted) crashes involved a police cruiser. Crashes between two police cruisers were excluded as they were too rare to make valid inferences. Among the total of 12,979,936 (weighted) drivers, 14% were cognitively distracted, 1.6% were distracted by an in-vehicle source, and the rest were not distracted. For police drivers in particular, 10.6% were cognitively distracted, and 7.1% were distracted by in-vehicle sources. A single ordered logit model was built including all the variables described previously. The estimated effects controlling for all the variables are reported in Tables 1 and 2. Table 2 focuses specifically on the distraction and driver types. Table 1 reports the results for all the other variables that we controlled for.

The results in Tables 1 and 2 are reported in terms of increasing injury severity. That is, the greater the estimated contrast coefficient and corresponding odds ratio, the higher the likelihood of more severe injuries. The estimates reported in Table 1 show that in general, among environmental factors, crashes in non daylight (OR=1.14), rural roads (OR=1.41), and curvy roads (OR=1.18) had higher odds of resulting in more severe injuries. In contrast, adverse weather (OR=0.86) and highway driving (OR=0.98) resulted in decreased odds. These findings were in accordance with (*12*), which focused only on teenage drivers. Crashes on intersections had a lower likelihood of resulting in more severe injuries than crashes on non intersections (OR=0.86). When a crash involved alcohol (OR=2.85) or speeding (OR=1.20), likelihood of more severe injuries increased. Angular crashes were more likely to result in more severe injuries than rear-end crashes (OR=1.74). This effect was in line with (*13*) and might be due to the potentially higher relative speeds in angular crashes and fewer side-protection systems in vehicles.

TABLE 1: Injury severity results for model covariates (excluding distraction and driver type, which are reported in Table 2)

Comparisons	Estimate*	Odds Ratio (OR)	95% Confidence Interval (CI)
Environmental conditions			
Non daylight vs. daylight	0.1350	1.14	1.14 – 1.15
Rural vs. urban	0.3447	1.41	1.41 – 1.42
Curvy vs. straight road	0.1670	1.18	1.18 – 1.19
Bad vs. good weather	-0.1544	0.86	0.85 – 0.86
Highway vs. non highway	-0.0176	0.98	0.98 – 0.99
Intersection vs. non intersection	-0.1516	0.86	0.85 – 0.87
Crash profile			
Alcohol vs. no alcohol	1.0471	2.85	2.82 – 2.88
Speeding vs. no speeding	0.1825	1.20	1.20 – 1.21
Angular vs. rear-end crash	0.5554	1.74	1.74 – 1.75
Occupants (drivers and passengers)			
Female vs. Male	0.5561	1.74	1.74 – 1.75
Seatbelt vs. no seatbelt	-0.6198	0.54	0.53 – 0.54
Front seat vs. back seat	0.1389	1.15	1.14 – 1.16
Young vs. middle age	-0.2956	0.74	0.74 – 0.75
Old vs. middle age	0.0584	1.06	1.05 – 1.07
Drivers' gender (baseline: both male)			
Female & male	-0.1012	0.90	0.90 – 0.91
Both female	-0.2155	0.81	0.80 – 0.81
Drivers' age (baseline: both middle age)			
Young & old	0.1977	1.22	1.21 – 1.23
Young & middle age	0.1568	1.17	1.17 – 1.17
Both young	0.1453	1.16	1.15 – 1.16
Middle age & old	0.1005	1.11	1.10 – 1.11
Both old	0.0440	1.05	1.03 – 1.06

* All estimates are significant at $p < .0001$

As expected, occupants' injury severity was significantly associated with occupants' age, gender, seating position, and seatbelt use (*13*). Female occupants were more likely to sustain more severe injuries than male occupants (OR=1.74). Using a seatbelt decreased the odds of more severe injuries (OR=0.54), whereas sitting in the front increased the odds (OR=1.15).

Compared to middle-age occupants, young occupants had lower odds of being more severely injured (OR=0.74), whereas old occupants had higher odds (OR=1.06).

Compared to the baseline of two male drivers, a female and a male (OR=0.90) drivers' crash and two female drivers' crash (OR=0.81) were likely to result in decreased injury severity. Compared to both middle-age drivers, young & old combination (OR=1.22) had the highest odds of severe injuries followed by young & middle age (OR=1.17), both young (OR=1.16), middle age & old (OR=1.11), and both old (OR=1.05). Several studies reveal that middle-age drivers are safer than young and old drivers (*13, 28*). Our results conform to previous research, but also highlight that crashes between a young and an old driver have the highest odds for severe injuries.

As reported in Table 2, in-vehicle distractions increased the likelihood of severe injuries observed in a crash when the distracted driver was a police officer (OR=2.40) or a civilian (1.29). That is, a crash which involved a police officer distracted by an in-vehicle source had a higher likelihood of resulting in more severe injuries than a crash which involved a non-distracted police officer. Similarly, a crash which involved a civilian driver distracted by an in-vehicle source had a higher likelihood of resulting in more severe injuries than a crash which involved a non-distracted civilian driver. The increase in odds was larger for police drivers compared to civilian drivers (OR= 2.40 as opposed to 1.29).

TABLE 2: Injury severity results for driver and distraction type

Comparisons	Estimate*	OR	95% CI
Police driver			
In-vehicle vs. no distraction	0.8758	2.40	2.19 – 2.64
Cognitive vs. no distraction	-1.0115	0.36	0.32 – 0.41
Civilian driver			
In-vehicle vs. no distraction	0.2556	1.29	1.28 – 1.30
Cognitive vs. no distraction	-0.0938	0.91	0.91 – 0.91
Police vs. civilian drivers			
No distractions (both drivers)	-0.1676	0.85	0.82 – 0.87
In-vehicle distractions (both drivers)	0.4527	1.57	1.44 – 1.72
Cognitive distractions (both drivers)	-1.0852	0.34	0.30 – 0.39
Distracted police vs. non-distracted civilian			
Police with in-vehicle distraction	0.7083	2.03	1.86 – 2.22
Police with cognitive distraction	-1.1790	0.31	0.27 – 0.35

* All estimates are significant at $p < .0001$ unless otherwise noted

In contrast to the effects of in-vehicle distractions, cognitive distractions decreased the likelihood of severe injuries. A crash which involved a cognitively distracted police officer had a lower likelihood of resulting in more severe injuries than a crash which involved a non-distracted police officer (OR=0.36). Similarly, a crash which involved a cognitively distracted civilian driver had a lower likelihood of resulting in more severe injuries than a crash which involved a non-distracted civilian driver (OR=0.91). The decrease in odds was larger for police officers (OR= 0.36 as opposed to 0.91).

Direct comparisons between police and civilian drivers revealed the following results. A crash which involved a non-distracted police driver resulted in less severe injuries than a crash which involved a non-distracted civilian driver (OR=0.85). A similar effect was observed for cognitive distractions. That is, a crash which involved a cognitively distracted police officer resulted in less severe injuries than a crash which involved a cognitively distracted civilian driver (OR=0.34). In contrast, a crash which involved a police officer distracted by an in-vehicle source resulted in more severe injuries than a crash which involved a civilian driver distracted by an in-vehicle source (OR=1.57).

To better illustrate these differences, Figure 1 presents odds ratios for different driver and distraction type combinations in comparison to non-distracted civilian drivers (baseline). Overall, our findings suggest that crashes which involve police drivers distracted by an in-vehicle source have the highest odds of resulting in more severe injuries.

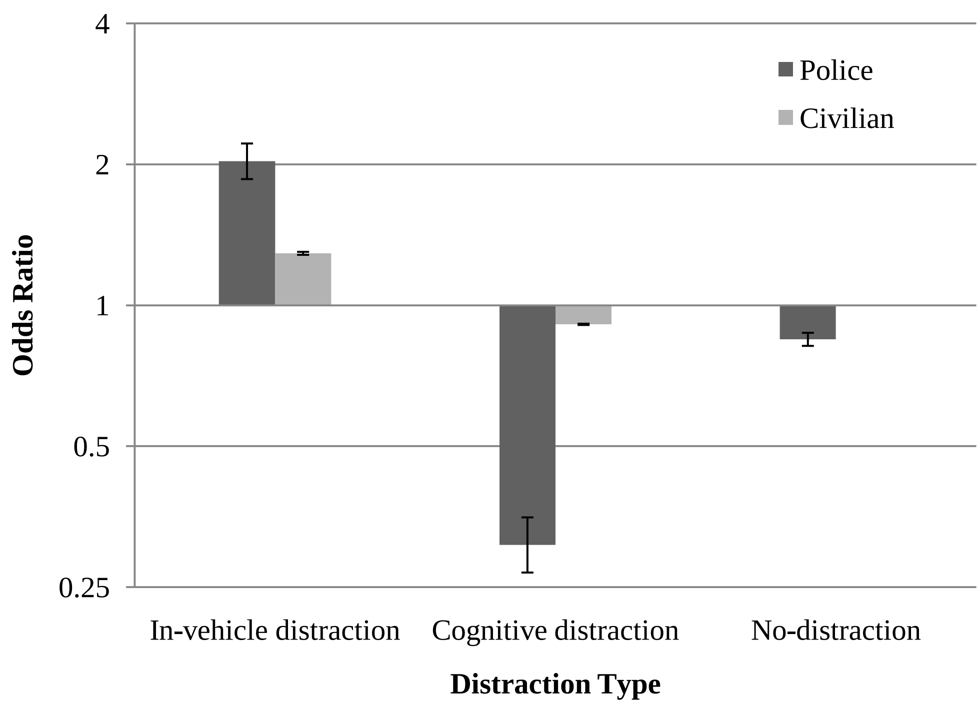

FIGURE 1: Injury severity odds ratios for different distraction and driver types (baseline: non-distracted civilian driver; error bars indicate 95% confidence intervals)

DISCUSSION

This paper reports the results of an ordered logit model built on GES data, a US national crash database, to investigate the likelihood of severe injuries when a crash involved distracted police drivers. In general, cognitive distractions were found to decrease injury severity, whereas in-vehicle distractions increased injury severity. In particular, crashes which involved police drivers distracted by in-vehicle sources were found to be more severe than crashes which involved civilian drivers distracted by in-vehicle sources. In contrast, crashes which involved non-distracted police drivers were less severe than crashes which involved non-distracted civilian drivers. A similar effect was observed for cognitive distractions. The underlying reasons for these findings should be assessed in future research. A crash database due to its observational nature does not lend itself to assessing causation. Crash data also do not provide the level of detail necessary to assess driver behavior at pre-crash moments.

Our results suggest that distractions due to in-vehicle sources have a more profound effect on the injury severities observed in police driver crashes compared to civilian driver crashes. One potential explanation for this finding relates to the devices integrated in police cruisers, such as a laptop, radio, as well as strobe and siren controls. These technologies potentially have greater sophistication and present greater physical and mental workload for drivers than traditional information sources (*29*). Potential mitigation strategies include a second police officer in the vehicle to perform non-driving related tasks (although this might result in significant staffing issues and/or an increase in passenger-related distractions) and improved human computer interaction (e.g., automatic scanning and identification of plate numbers). Although efforts have been made to integrate cruiser controls into a single graphical user interface (*30*), the effectiveness of such a strategy for mitigating police driver distraction is not properly addressed.

Although we revealed important results regarding distractions caused by in-vehicle sources, our study has limitations. In-vehicle distraction category used in this study includes all possible in-vehicle sources of distraction (devices, controls, eating, etc.). We aggregated these sources under one category because the in-vehicle environment of passenger vehicles does not match to that of police cruisers and GES distraction categories are designed more towards civilian drivers' activities. Thus, our findings on increased injury severity with in-vehicle distractions should not be solely attributed to in-vehicle technologies. Further research is needed to breakdown the effects of various in-vehicle distraction sources.

We used 2003 – 2008 GES dataset because it has the best driver distraction information for the longest period of time at the national level. Although police-involved crashes constitute a small fraction of the sample population, the mere size of the dataset made it possible to draw inferences on crashes with distracted police drivers. A general limitation with the use of crash databases is that these data are based on police reports and may present a biased sample (*31*). For example, driver distraction might be underreported, especially if there are fatalities. This underreporting issue had been acknowledged previously, and several states are making efforts to collect better data on driver distraction (*32*). Moreover, crashes which involve a police officer might be reported differently than civilian crashes. For example, civilian crashes with no injuries might be underreported as some of these crashes might be settled in private. Underreporting of civilian crashes with no injuries would affect our model results, in particular the comparisons between police and civilian drivers, biasing the injury severity of civilian crashes towards larger severities.

Previous research revealed that injury severity, as well as crash risk, has a U-shape relationship with age (*13, 28*). That is, crashes which involve young and old drivers result in more severe injuries compared to crashes which involve middle-age drivers. Our results also reveal the same trend. However, previous research did not take into account the age of all drivers in a crash. In our analysis, we focused on two-vehicle crashes with both drivers' information on one record. Thus, occupants' injury severities were modeled to be affected by both drivers' characteristics, which is a more realistic assumption. Interestingly, we revealed that injury severity was highest when a crash involved a young and an old driver. Further research is needed to reveal the underlying reasons for this interesting finding.

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