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A Comparative Analysis of Factors Affecting the Frequency and Severity of Freight-Involved and Non-Freight Crashes on a Major Freight Corridor Freeway

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Abstract
Traffic crashes cost society billions of dollars each year as a result of property damage, injuries, and fatalities. Additionally, traffic crashes have a negative impact on mobility, as they are a primary cause of non-recurring delay. With the Interstate 10 corridor between the ports of Los Angeles and Houston being one of the most vital links for goods movement across the United States, safety and mobility along this freeway, particularly for freight traffic, are of significant concern. This study, which utilized six years of crash data from the state of Arizona, explores factors affecting the frequency and severity of crashes along the Arizona portion of the I-10 corridor, with a particular focus on freight-related crashes. The safety performance along the I-10 is analyzed through the development of crash frequency and severity prediction models using integrated crash, roadway, traffic, and environmental data. Negative binomial and ordered logit models, with the incorporation of random parameters, were estimated to provide a detailed understanding of factors associated with freight-involved crashes and how they compare to non-freight crashes in terms of frequency and severity. The results showed that several roadway- crash-, vehicle-, and person-related variables were associated with the frequency and/or severity of crashes along the study corridor. These findings provide important insights which can be used to develop or plan countermeasures aimed at improving the safety and efficiency of freight travel, which may include new ITS technologies, and targeted educational and enforcement campaigns.

Goods movement across the US is one of the most significant factors for economic growth in the United States. Between 1993 and 2002, the national gross domestic product (GDP) increased by 33% while the value of freight shipments increased by 45% (*1*). In 2013, the US transportation system moved a daily average of about 55 million tons of freight, valued at more than $49.3 billion, with trucks transporting about 70% of that total (*2*).

The country has reached an important crossroads: with more people and goods taking to the roads, motor vehicle deaths on the nation's roadways are on a historic 14% rise from 2014 to 2016 (*3*). Additionally, national crash statistics from 2015 show that a larger percentage of large truck and bus crashes result in fatalities than other crash types (*4*). The National Safety Council estimates the current comprehensive cost of a motor vehicle death to be $10,082,000 (*5*). Given these recent statistics, it is clear there is a strong need for improving traffic safety measures on vital freight corridors.

Many states have already begun to take steps towards reducing friction between passenger and commercial vehicles. For example, the I-95 Corridor Coalition involves 15 different states that all work together to share valuable information with the shared goal of enhancing mobility, safety, and efficiency between each state (*6*). In Arizona, the newly formed I-10 Corridor Coalition shares a similar goal with California, New Mexico, and Texas (*7*). Both the west and east sections of the I-10 in Arizona are considered by the Arizona Department of Transportation (ADOT) to be vital for the overall health of the statewide transportation system (*8*). However, no in-depth analysis of freight-involved

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crashes on the entirety of Arizona's portion of the I-10 has been completed. This study aims to fill that void and provide important information which may be useful in planning future traffic safety improvements.

Several studies have been completed across the US and Canada that have examined factors affecting either the frequency or severity of large truck crashes with most focusing primarily on injury severity as a function of crash reported variables. In 2015, a study was completed in Ontario, Canada that used a general estimating equation model to compare frequency predictions for truck-involved and non-truck-involved crashes (*9*). The study concluded that wider lane widths increased frequency, higher truck percentage decreased frequency, and higher speed limits also decreased frequency in truck-involved crashes. Additionally, it was found that in two successive years, at any given location, there was no direct correlation between truck-involved crashes and non-truck-involved crashes (*9*).

Another study, which was completed in 2017, used multinomial logit and negative binomial models under the Bayesian estimation framework to analyze crash severity and frequency, respectively (*10*). They found that inclement weather conditions increased the frequency and severity of truck-involved crashes (*10*). The results also showed that higher speed limits reduced the frequency of truck crashes and that dark lighting conditions and rural terrains increased the severity of truck-involved crashes (*10*). Significant safety needs were highlighted in two 2017 I-10 performance reports by ADOT, in which 11 out of 24 study segments were identified as having a "high" need for safety improvements (*8*, *11*).

To gain further insights, this study utilizes crash data from 2010 to 2015, roadway and traffic characteristics, and two different statistical approaches to analyze factors which may be associated with high crash frequencies and severe injuries on the I-10 in Arizona. With the entire freeway through Arizona being combined and evaluated as a freight corridor, the findings of this study may be used for future safety improvements to enhance freight safety and mobility.

Data Description

The data for this study were acquired from ADOT and included a record of all reported crashes in the state of Arizona from 2010 to 2015, as well as geometric and traffic volume data from ADOT's Multimodal Planning Division (MPD). These data were filtered to only include incidents and roadway characteristics on the I-10 through Arizona. To gain a full understanding of crashes on the I-10 and to satisfy the data needs for the frequency models and severity models, three different datasets were created.

The first dataset was designed for the frequency model and consisted of 264 predefined segments with separate segments for the eastbound and westbound directions on the I-10. Annual crashes were then linked to the segments by GPS coordinates provided in the crash reports, resulting in a total of 1,584 segment-year cases. The crashes assigned to each segment were classified as "freight-involved" or "non-freight" by filtering crashes with five unique body-style identifiers that encompass tractor-trailers, box trucks, and auto carriers.

Geometric characteristics were then assigned to each segment by intersecting several different geometric layers in ArcMap (*12*) with the predefined study segments. Because the purpose of this study was to compare factors affecting freight-involved crashes to factors affecting non-freight crashes, a separate dependent variable was incorporated into the dataset that included all non-freight-involved crashes on the I-10 over the study period. These crash counts were also linked to the same segments by using ArcMap. For this study, it was assumed that the geometric characteristics for each segment stayed constant during the study period. However, the Annual Average Daily Traffic (AADT) counts and truck percent varied from year to year. Ultimately, the 'freight-involved' dataset included 5,695 crashes while the 'non-freight' dataset (which included all non-freight crashes on the I-10 over the study period) included 30,037 crashes.

During the frequency modeling process defined in the following section, many of the continuous geometric variables such as number of lanes, median width, and median type were reclassified as binary indicator variables (0 or 1). Since the study section of the I-10 spans from the western border to the eastern border of Arizona and passes through urban areas with high traffic volumes and unique geometric and road user characteristics, it is important to account for this variation in the model. This was accomplished by identifying each segment in the urban Phoenix area with a high occupancy vehicle lane as the indicator variable "Phoenix." Descriptive statistics for variables utilized in the frequency models are presented in Table 1.

For the datasets utilized in the severity analyses, each person in each crash on the I-10 was recorded as a unique observation. Geometric characteristics were again assigned using ArcMap and the GPS coordinates of the crash that each individual person was involved in. The freight-involved severity dataset used the same freight classifications described previously and consisted only of persons in a freight-involved crash (a total of 14,148 observations). The non-freight severity dataset consisted of all persons involved in crashes on the I-10, excluding those that were freight-involved, for a total of 71,051 observations. For the severity models, the ordered

Table 1. Descriptive Statistics for Frequency Model Variables

Roadway characteristics	Mean	Std. dev.	Min.	Max.
Segment length (miles)	2.96	3.05	0.19	15.68
AADT	45,848	38,963	4,350	171,154
Ln(AADT)	10.32	0.95	8.38	12.05
Cable barrier*	0.10	0.30	0.00	1.00
Concrete barrier*	0.30	0.46	0.00	1.00
No barrier*	0.61	0.49	0.00	1.00
Median width <39 Ft*	0.27	0.44	0.00	1.00
Median width 40–79 Ft*	0.58	0.49	0.00	1.00
Median width >80 Ft*	0.16	0.37	0.00	1.00
Right shoulder (Ft)	10.64	1.93	6.63	22.71
Left shoulder (Ft)	7.63	3.70	3.00	18.12
3 or 4 Lanes*	0.41	0.49	0.00	1.00
5 or 6 Lanes*	0.16	0.37	0.00	1.00
2 Lanes*	0.42	0.49	0.00	1.00
Speed limit 45 or 55*	0.12	0.32	0.00	1.00
Speed limit 65*	0.42	0.49	0.00	1.00
Speed limit 75*	0.46	0.50	0.00	1.00
Degree of curvature	0.02	0.17	0.00	1.68
Percent grade	0.74	0.53	0.00	2.22
Truck percent	13.70	11.10	1.82	54.66
Phoenix indicator*	0.30	0.46	0.00	1.00
Freight-involved crashes[a]	3.60	3.65	0.00	24.0
Non-Freight crashes[b]	19.60	26.53	0.00	243

*Binary indicator variable (i.e., 0 or 1).
[a]Dependent variable for the freight-involved crashes only model.
[b]Dependent variable for the non-freight model.

discrete variable, injury status, was modeled as the dependent variable. The injury status levels are described by the Arizona Crash Report Forms Instruction Manual as follows (*13*):

- 5-Injury: Fatal Injury (K-injury)
- 4-Injury: Incapacitating Injury (A-injury)
- 3-Injury: Non-Incapacitating Injury (B-injury)
- 2-Injury: Possible Injury (C-injury)
- 1-No Injury (O—No injury)

In the two severity datasets, all variables were recoded into binary indicator variables. For example, the "summer months" variable takes the value of 1 if the crash occurred during a summer month (i.e., June–August), otherwise, it takes the value of 0. Also of note, if a variable was initially recorded as "unknown" or "not reported" then the entire observation was omitted from the final models. Unlike the frequency models, the severity model framework allows for incident-, unit-, and person-level characteristics, as well as the geometric characteristics to be included as independent variables. The body style indicator variables for persons in freight vehicles and persons in passenger vehicles are important in this study as they provide insight into the safety impact of large trucks sharing the road with smaller passenger vehicles. Summary statistics for the freight-involved severity dataset are presented in Table 2 and summary statistics for the non-freight severity dataset are presented in Table 3. Again, note that all variables contained in Tables 2 and 3 are binary indicator variables.

Analysis Methodology

Two different types of model were used for this study. The first was a random parameters (RP) negative binomial regression model, used for analyzing factors which may affect the frequency of crashes. The second was an RP ordered logit model, used for analyzing factors which may affect the severity of crashes (in terms of injury outcomes). The two-model approach and the combination of different data sources helps create a detailed understanding of factors involved in freight crashes and non-freight crashes on a major freight corridor freeway.

Crash Frequency Model: Negative Binomial Regression

Using a negative binomial model for crash frequency predictions has been proven to be effective in past studies (*10*, *14*, *15*), and it is one of the most popular methods for the development of Safety Performance Functions

Table 2. Summary Statistics for Freight-Involved Severity Model Variables

*Total observations = 14,148	Freight-involved crash occupant injuries by severity level					
	No injury	C-injury	B-injury	A-injury	K-fatal	Total
Environmental characteristics						
Summer months	2,877 (83%)	232 (7%)	259 (8%)	42 (1%)	36 (1%)	3,446
Other months	8,966 (83%)	735 (7%)	797 (7%)	134 (1%)	70 (<1%)	10,702
Blowing sand and/or dust	140 (65%)	16 (7%)	38 (18%)	17 (8%)	6 (3%)	217
Other weather conditions	11,652 (84%)	948 (7%)	1,014 (7%)	159 (1%)	100 (<1%)	13,873
Dark light conditions	3,015 (80%)	295 (8%)	364 (10%)	64 (2%)	44 (1%)	3,782
First harmful event						
Collision with concrete barrier	89 (73%)	10 (8%)	17 (14%)	4 (3%)	2 (2%)	122
Rollover	146 (43%)	38 (11%)	126 (37%)	18 (5%)	12 (4%)	340
Jackknife	20 (91%)	2 (9%)	0 (0%)	0 (0%)	0 (0%)	22
Other first harmful events	11,586 (85%)	917 (7%)	913 (7%)	154 (1%)	92 (<1%)	13,662
Collision manner						
Single vehicle	826 (77%)	54 (5%)	160 (15%)	19 (2%)	8 (1%)	1,067
Angle	380 (75%)	57 (11%)	53 (10%)	12 (2%)	5 (1%)	507
Head on	49 (53%)	13 (14%)	7 (8%)	9 (10%)	15 (16%)	93
Sideswipe same direction	4,577 (91%)	223 (4%)	210 (4%)	23 (<1%)	13 (<1%)	5,046
Sideswipe opposite direction	25 (69%)	1 (3%)	8 (22%)	1 (3%)	1 (3%)	36
Other collision manners	4,549 (79%)	563 (10%)	543 (9%)	78 (1%)	37 (<1%)	5,770
Body style						
Freight vehicle	6,404 (89%)	282 (4%)	397 (6%)	57 (1%)	33 (<1%)	7,173
Passenger vehicle	4,966 (78%)	631 (10%)	600 (9%)	99 (2%)	62 (1%)	6,358
Motorcycle	7 (23%)	2 (7%)	10 (33%)	8 (27%)	3 (10%)	30
Other vehicle	206 (89%)	14 (6%)	8 (3%)	4 (2%)	0 (0%)	232
Event sequence						
Cross median	35 (41%)	10 (12%)	24 (28%)	7 (8%)	10 (12%)	86
Run-off-road right	505 (60%)	82 (10%)	192 (23%)	31 (4%)	30 (4%)	840
Run-off-road left	567 (57%)	129 (13%)	233 (23%)	42 (4%)	21 (2%)	992
Other event sequences	10,807 (87%)	762 (6%)	646 (5%)	100 (1%)	47 (<1%)	12,362
Age and gender						
Age 24 or less	2,420 (82%)	219 (7%)	254 (9%)	37 (1%)	29 (1%)	2,959
Age 65 or up	730 (79%)	65 (7%)	86 (9%)	25 (3%)	16 (2%)	922
Other ages	8,458 (85%)	666 (7%)	706 (7%)	113 (1%)	61 (<1%)	10,004
Female	3,351 (78%)	465 (11%)	389 (9%)	72 (2%)	28 (1%)	4,305
Other genders	8,368 (86%)	501 (5%)	666 (7%)	104 (1%)	78 (<1%)	9,717
Safety device and violation						
Safety device used	11,106 (85%)	895 (7%)	886 (7%)	122 (1%)	43 (<1%)	13,052
Drugs or alcohol used	56 (41%)	8 (6%)	18 (13%)	11 (8%)	42 (31%)	135
Roadway characteristics						
Median width <20 Ft	2,357 (87%)	191 (7%)	125 (5%)	15 (1%)	6 (<1%)	2,694
Median width >80 Ft	1,548 (78%)	132 (7%)	238 (12%)	40 (2%)	35 (2%)	1,993
Other median widths	7,938 (84%)	644 (7%)	693 (7%)	121 (1%)	65 (<1%)	9,461
Speed limit 75	3,563 (79%)	241 (5%)	510 (11%)	116 (3%)	75 (2%)	4,505
Other speed limits	8,280 (86%)	726 (7%)	546 (6%)	60 (<1%)	31 (<1%)	9,643
Right shoulder width <10 Ft	1,668 (78%)	129 (6%)	267 (12%)	51 (2%)	28 (1%)	2,143
Other right shoulder widths	10,175 (85%)	838 (7%)	789 (7%)	125 (1%)	78 (<1%)	12,005
Left shoulder width <4 Ft	3,176 (80%)	230 (6%)	406 (10%)	76 (2%)	60 (2%)	3,948
Other left shoulder widths	8,667 (85%)	737 (7%)	650 (6%)	100 (1%)	46 (<1%)	10,200
Percent of trucks >20%	1,012 (75%)	73 (5%)	195 (14%)	37 (3%)	28 (2%)	1,345
Level roadway	11,039 (84%)	905 (7%)	950 (7%)	154 (1%)	94 (1%)	13,142
Other roadway grade	767 (80%)	56 (6%)	103 (11%)	22 (2%)	12 (1%)	960
Grand total	11,843 (84%)	967 (7%)	1056 (7%)	176 (1%)	106 (<1%)	14,148

(i.e., crash prediction models) with rare events (*16*). The negative binomial regression model is derived from the general form of the Poisson regression model, with the Poisson parameter being rewritten as shown in Equation 1 (*17*):

$$\lambda_i = EXP(\beta_0 + \beta_1 X_1 + \beta_i X_i + \varepsilon_i) \quad (1)$$

Where:

λ_i: Poisson parameter for road segment i (i.e., predicted number of annual crashes for road segment i)

Table 3. Summary Statistics for Non-Freight Severity Model Variables

*Total observations = 71,051	Non-freight crash occupant injuries by severity level					
	No injury	C-injury	B-injury	A-injury	K-fatal	Total
Environmental characteristics						
Summer months	13,356 (83%)	1,308 (8%)	1,230 (8%)	225 (1%)	69 (<1%)	16,188
Other months	45,563 (83%)	4,689 (9%)	3,816 (7%)	634 (1%)	161 (<1%)	54,863
Blowing sand and/or dust	179 (82%)	7 (3%)	32 (15%)	0 (0%)	0 (0%)	218
Other weather conditions	58,605 (83%)	5,975 (8%)	5,000 (7%)	855 (1%)	229 (<1%)	70,664
Dark light conditions	13,476 (80%)	1,416 (8%)	1,514 (9%)	334 (2%)	116 (<1%)	16,856
First harmful event						
Collision with concrete barrier	1187 (67%)	251 (14%)	294 (16%)	44 (2%)	8 (<1%)	1,784
Rollover	946 (35%)	399 (15%)	975 (36%)	285 (10%)	112 (4%)	2,717
Jackknife	108 (94%)	4 (3%)	3 (3%)	0 (0%)	0 (0%)	115
Other first harmful events	56,676 (85%)	5,343 (8%)	3,774 (6%)	530 (<1%)	110 (<1%)	66,433
Collision manner						
Single vehicle	8,587 (72%)	953 (8%)	1,812 (15%)	457 (4%)	148 (1%)	11,957
Angle	1,299 (80%)	156 (9%)	162 (10%)	30 (2%)	0 (0%)	1,647
Head on	198 (62%)	40 (13%)	50 (16%)	16 (5%)	15 (5%)	319
Sideswipe same direction	10,257 (90%)	586 (5%)	436 (4%)	54 (<1%)	12 (<1%)	11,345
Sideswipe opposite direction	102 (80%)	12 (9%)	11 (9%)	2 (2%)	0 (0%)	127
Other collision manners	35,902 (84%)	4,117 (10%)	2,406 (6%)	257 (<1%)	28 (<1%)	42,710
Body style						
Passenger vehicle	53,916 (83%)	5,551 (8%)	4,468 (7%)	674 (1%)	191 (<1%)	64,800
Motorcycle	118 (19%)	84 (14%)	288 (47%)	104 (17%)	15 (2%)	609
Other vehicle	1,616 (91%)	82 (5%)	49 (3%)	24 (1%)	11 (<1%)	1,782
Event sequence						
Cross median	215 (56%)	49 (13%)	74 (19%)	29 (8%)	15 (4%)	382
Run-off-road right	2,578 (59%)	488 (11%)	926 (21%)	265 (6%)	90 (2%)	4,347
Run-off-road left	3,128 (61%)	573 (11%)	1,044 (20%)	267 (5%)	119 (2%)	5,131
Other event sequences	53,436 (86%)	5,004 (8%)	3,245 (5%)	377 (<1%)	43 (<1%)	62,105
Age and gender						
Age 24 or less	19,227 (84%)	1,641 (7%)	1,622 (7%)	259 (1%)	52 (<1%)	22,801
Age 65 or up	3,207 (81%)	307 (8%)	327 (8%)	62 (2%)	46 (1%)	3,949
Other ages	35,444 (82%)	3,979 (9%)	3,067 (7%)	536 (1%)	132 (<1%)	43,158
Female	25,202 (80%)	3,287 (10%)	2,420 (8%)	375 (1%)	92 (<1%)	31,376
Other genders	33,374 (85%)	2,706 (7%)	2,624 (7%)	484 (1%)	138 (<1%)	39,326
Safety device and violation						
Safety device used	56,811 (84%)	5,666 (8%)	4,454 (7%)	542 (<1%)	79 (<1%)	67,552
Drugs or alcohol used	385 (52%)	60 (8%)	134 (18%)	46 (6%)	115 (16%)	740
Roadway characteristics						
Median width <20 Ft	13,416 (85%)	1,335 (8%)	925 (6%)	123 (<1%)	26 (<1%)	15,825
Median width >80 Ft	3,742 (75%)	414 (8%)	635 (12%)	181 (4%)	48 (1%)	5,020
Other median widths	41,761 (83%)	4,248 (8%)	3,486 (7%)	555 (1%)	156 (<1%)	50,206
Speed limit 75	9,483 (78%)	792 (6%)	1,405 (12%)	374 (3%)	139 (1%)	12,193
Other speed limits	49,436 (84%)	5,205 (8%)	3,641 (6%)	485 (<1%)	91 (<1%)	58,858
Right shoulder width <10 Ft	4,895 (76%)	502 (8%)	760 (12%)	203 (3%)	67 (1%)	6,427
Other right shoulder widths	54,024 (84%)	5,495 (9%)	4,286 (7%)	656 (1%)	163 (<1%)	64,624
Left shoulder width <4 Ft	8,769 (76%)	908 (8%)	1,365 (12%)	361 (3%)	123 (1%)	11,526
Other left shoulder widths	50,150 (84%)	5,089 (9%)	3,681 (6%)	498 (<1%)	107 (<1%)	59,525
Percent of trucks >20%	1,829 (71%)	164 (6%)	407 (16%)	134 (5%)	46 (2%)	2,580
Level roadway	56,179 (83%)	5,646 (8%)	4,632 (7%)	782 (1%)	203 (<1%)	67,442
Other roadway grade	2,502 (75%)	344 (10%)	400 (12%)	74 (2%)	26 (<1%)	3,346
Grand total	58,919 (83%)	5,997 (8%)	5,046 (7%)	859 (1%)	230 (<1%)	71,051

β_i: vector of estimable parameters

X_i: vector of explanatory (independent) variables (i.e., roadway, traffic, environmental characteristics, etc.,)

$EXP(\varepsilon_i)$: gamma-distributed error term

The error term, $EXP(\varepsilon_i)$ with a mean 1 and variance α, allows the variance to differ from the mean as shown in Equation 2 below (*17*):

$$VAR[y_i] = E[y_i] + \alpha E[y_i]^2 \tag{2}$$

Where:

$VAR[y_i]$: variance of crashes per year per segment

$E[y_i]$: mean of crashes per year per segment

α: over-dispersion parameter estimated with negative binomial model

A high α value indicates the presence of greater over-dispersion in the model, and as the over-dispersion parameter (α) approaches zero, the negative binomial model regresses to the Poisson model. The over-dispersion parameters for both crash frequency models developed as part of this study were statistically significant, indicating the appropriateness of the use of NB models. Ultimately, the model results are presented as the parameter estimates, β_i, for each explanatory variable, along with the standard error and *p*-value. In interpreting model results, negative β_i values represent an expected reduction in crash frequency, and positive values represent an expected increase in crash frequency. The results of the negative binomial models can give researchers a better understanding of how traffic, roadway, environmental, and other characteristics affect the expected frequency of crashes.

Crash Severity Analysis: Ordered Logit Model

Several past studies have successfully utilized discrete outcome models such as the ordered logit model in past traffic safety studies (*18*, *19*). The ordered logit model is often used for estimating the effect that explanatory variables have on the outcome of an ordered discrete variable: injury severity in this case of this study. The ordered logit model is derived by the unobserved variable, Z, which is used as the basis for modeling the ordinal ranking of data (*17*). The Z variable is specified as a linear function for each observation of occupant injury severity (*17*).

$$Z = \beta X + \varepsilon \quad (3)$$

Where:

X: vector of variables determining the discrete ordering for each occupant injury severity observation

β: vector of estimable parameters

ε: disturbance term

Considering this specification, the observed injury severity outcomes, y, is defined by the following thresholds:

$$\begin{aligned} y &= 1 \quad \text{if } z \leq \mu_0, \\ y &= 2 \quad \text{if } \mu_0 < z \leq \mu_1, \\ y &= 3 \quad \text{if } \mu_1 < z \leq \mu_2, \\ y &= 4 \quad \text{if } \mu_2 < z \leq \mu_3 \\ y &= 5 \quad \text{if } z > \mu_3, \end{aligned} \quad (4)$$

Where:

μ_i: estimable threshold parameters that define y, which corresponds to the ordered injury severity categories.

The thresholds, μ, are estimated along with the model parameters β_i. The first threshold (i.e., μ_0) is set to zero without loss of generality, and the error term, ε, is assumed to be logistically distributed across observations. Under this assumption, and by setting μ_0 equal to zero, the outcome probabilities become (*17*):

$$P(y = i) = \mathrm{F}(u_i - \beta X) - \mathrm{F}(u_{i-1} - \beta X) \quad (5)$$

Where:

F: Cumulative distribution function of the logistic distribution defining ε

μ_i: upper threshold for injury severity i

μ_{i-1}: lower Threshold for Injury severity i

Since each person is considered as a unique observation, panel data were incorporated into the severity models to account for potential correlation among the injury outcomes of persons in the same vehicle (i.e., potential intra-vehicle correlation). To achieve this framework, each occupant observation is assigned to a unique vehicle ID within the dataset. Further information regarding panel data is provided elsewhere (*17*).

Random Parameters

Given the variability of crash data, it was determined that random parameters would be considered in the negative binomial models and the ordered logit models. Random parameters have been proven to be effective in providing a better model fit when considering complex, unobserved, crash variables (*20*, *21*). The random parameters framework allows certain estimable parameters that exhibit significant variability (as evidenced by a significant standard deviation) to vary across observations. This also accounts for unobserved heterogeneity within the explanatory variables themselves. For example, there may be unobservable differences across the driving population such as risk-taking behavior and physiological factors (*17*). The random parameters framework alters both models as such:

$$\beta_i = \beta + \omega_n \quad (6)$$

where:

β_i: estimable parameter

ω_n: randomly distributed term (i.e., normally distributed with mean zero and variance σ^2)

Instead of randomly drawing parameters from their respective normal distributions, it is common practice to use Halton draws which accomplish the same result with far fewer draws (*22–24*). Due to a high number of observations and random parameters in the random parameter ordered logit models, 100 Halton draws were found to be adequate for this analysis.

In addition to the ordered logit model estimation, marginal effects were also estimated for additional insight in the severity analysis. The magnitude and sign of each marginal effect help to illustrate the effect that each variable has on severity outcomes (*17*). Because each variable in the random parameter ordered logit models were classified as a binary indicator, the numerical marginal effects represent the change in probability of an injury severity level when the corresponding indicator variable is changed from 0 to 1. Further information on the calculation of marginal effects is provided elsewhere (*17*). All models in this study were developed using the statistical software NLOGIT 5 (*25*).

Results and Discussion

The results of the random parameters negative binomial models (frequency models) are presented in Table 4. As described in the previous section, the random parameter framework allowed certain estimable parameters to vary across observations and this is represented in the results table with each random parameter having its own standard deviation, standard error, and *p*-value. Ultimately, the random parameters models provided a superior fit based on log likelihood ratio tests. The model results are interpreted such that a positive parameter, β, indicates that variable is associated with an increase in crash frequency for any given segment. For example, as the continuous variable, segment length, increases then the expected number of crashes at that segment would increase as well. Conversely, negative parameters represent an expected decrease in crash frequency. It is important to note that to have more uniform significant digits

Table 4. Results for the Random Parameter Negative Binomial Frequency Models

Freight-involved model	*B*	Std. error	*p*-value	Std. dev.	Std. error	*p*-value
Intercept	−7.138	0.852	<.001	0.113	0.017	<.001
Segment length*	0.184	0.008	<.001			
Ln(AADT)	0.704	0.073	<.001	0.014	0.002	<.001
Cable barrier*	0.180	0.102	.076			
Concrete barrier	0.237	0.089	.008	0.277	0.029	<.001
Median width < 39 (Ft)*	−0.181	0.058	.002			
Median width >80 (Ft)*	0.034	0.061	.575			
Right shoulder (Ft)*	0.002	0.011	.853			
Left shoulder (Ft)	−0.032	0.009	.001	0.007	0.002	.001
3 or 4 Lanes*	0.071	0.076	.347			
5 or 6 Lanes	−0.140	0.101	.167	0.324	0.035	<.001
Speed limit 65*	0.334	0.086	<.001			
Speed limit 75*	0.490	0.088	<.001			
Degree of curvature*	0.222	0.098	.023			
Percent grade	0.121	0.038	.002	0.137	0.019	<.001
Truck percent*	−0.006	0.004	.166			
Phoenix indicator*	0.437	0.095	<.001			
Over-dispersion**	0.117	1.101	<.001			
Non-freight model	β	Std. error	*p*-value	Std. dev.	Std. error	*p*-value
Intercept	−10.663	0.608	<.001	0.167	0.012	<.001
Segment length*	0.187	0.006	<.001			
Ln(AADT)	1.187	0.052	<.001	0.020	0.001	<.001
Cable barrier*	0.190	0.069	.006			
Concrete barrier	0.306	0.061	<.001	0.250	0.020	<.001
Median width <39 (Ft)*	−0.229	0.041	<.001			
Median width >80 (Ft)*	−0.267	0.043	<.001			
Right shoulder (Ft)*	−0.024	0.008	.004			
Left shoulder (Ft)	−0.016	0.007	.018	0.007	0.001	<.001
3 or 4 Lanes*	−0.132	0.052	.011			
5 or 6 Lanes	−0.312	0.071	<.001	0.266	0.025	<.001
Speed limit 65*	0.795	0.059	<.001			
Speed limit 75*	1.002	0.061	<.001			
Degree of curvature*	0.417	0.068	<.001			
Percent grade	0.133	0.026	<.001	0.222	0.013	<.001
Truck percent*	−0.018	0.003	<.001			
Phoenix indicator*	0.219	0.065	.001			
Over-dispersion**	0.128	0.445	<.001			

*Fixed Parameter in RP Model.

**Over-dispersion parameter for the negative binomial model framework.

Table 5. Results for the Freight-Involved Random Parameter Ordered Logit Severity Model

Variable	β	Std. error	p-value	Std. dev.	Std. error	p-value
Constant	−1.571	0.180	<.001	1.956	0.045	<.001
Summer months	−0.135	0.083	.101	1.227	0.071	<.001
Dust storm	1.113	0.267	<.001	2.282	0.258	<.001
Dark light conditions*	0.467	0.072	<.001			
Collision with concrete barrier	2.097	0.467	<.001	3.575	0.482	<.001
Rollover*	3.703	0.226	<.001			
Jackknife*	−2.120	0.914	.020			
Single vehicle*	−1.942	0.186	<.001			
Angle	−0.979	0.192	<.001	3.282	0.179	<.001
Head on	0.994	0.322	.002	2.694	0.329	<.001
Sideswipe same direction	−2.064	0.089	<.001	0.823	0.067	<.001
Sideswipe opposite direction	1.286	0.504	.011	1.381	0.544	.011
Motorcycle*	8.796	0.504	<.001			
Passenger vehicle*	1.949	0.081	<.001			
Cross median*	1.972	0.305	<.001			
Run-off-road right	2.164	0.128	<.001	2.149	0.112	<.001
Run-off-road left	2.426	0.119	<.001	1.264	0.094	<.001
Age 24 or less	−0.645	0.084	<.001	1.469	0.074	<.001
Age 65 or up	0.317	0.134	.018	1.429	0.120	<.001
Female*	0.740	0.068	<.001			
Safety device used*	−1.769	0.110	<.001			
Drugs or alcohol used	1.395	0.302	<.001	4.979	0.382	<.001
Median width <20 Ft*	−0.356	0.093	<.001			
Median width >80 Ft*	0.273	0.116	.019			
Speed limit 75	−0.345	0.112	.002	1.542	0.064	<.001
Right shoulder width <10 Ft	0.167	0.111	.133	0.263	0.078	.001
Left shoulder width <4 Ft	−0.836	0.123	<.001	1.524	0.069	<.001
Percent of trucks >20%	0.552	0.126	<.001	0.887	0.104	<.001
Level roadway*	−0.323	0.116	.006			
Threshold 1	1.379	0.039	<.001			
Threshold 2	5.003	0.110	<.001			
Threshold 3	7.264	0.198	<.001			
Restricted log likelihood (LL)	−6334.221					
Final LL for fixed model	−5872.399					
Final LL for RP model	−5820.096					

*Fixed parameter in RP model.

in the results, the natural log of AADT was used instead of AADT itself.

The results of the random parameter ordered logit models (severity models) and the associated marginal effects are presented in Tables 5 through 8. In total, 16 of the total 28 final variables included in the freight-involved random parameter model exhibited significant variability. During the modeling process, the variables with significant variability were retained as random. Variables that had statistically significant parameters but non-significant standard deviations were retained as fixed parameters. Variables that did not have significant parameters or significant variability were not included in the final models. Similar to the negative binomial model, the ordered logit model results are interpreted with positive parameters indicating an increase in the probability of the most severe injury severity outcome, and vice versa for negative parameter estimates.

While the marginal effects of several variables are small, when the costs of severe motor vehicle crashes (*5*) are considered, even a slight increase in the risk of severe injury can cost society millions of dollars over the course of several years. It is also important to note that these effects are compounded over the entire I-10 corridor through Arizona and thus many small risks can become one big problem over time.

Negative Binomial Frequency Model Results Discussion

Length and AADT had positive effects for both freight and non-freight crashes (i.e., greater segment lengths and AADT increased crash frequency) which is both intuitive and well supported by many past traffic safety studies. These two variables are also the standard for developing base safety performance functions (SPFs) and the parameter estimates and constant terms presented in both

Table 6. Marginal Effects for the Freight-Involved RP Ordered Logit Model

Variable	1-no injury	2-injury	3-injury	4-injury	5-fatal
Summer months	0.00337*	−0.00249*	−0.00086*	−0.10013	−0.10014
Dust storm	−0.04936***	0.03593***	0.01307**	0.00003**	0.00004**
Dark light conditions	−0.01345***	0.00991***	0.00345***	0.00009***	0.00001***
Collision with concrete barrier	−0.15382**	0.10816**	0.04436**	0.00116*	0.00013*
Rollover	−0.47921***	0.28201***	0.19059***	0.00591***	0.00069***
Jackknife	0.02333***	−0.01732***	−0.00585***	−0.00014***	−0.67795
Single vehicle	0.02656***	−0.01969***	−0.00669***	−0.00017***	−0.77646
Angle	0.01700***	−0.01260***	−0.00429***	−0.00011***	−0.4982
Head on	−0.04171**	0.03043**	0.01098**	0.00028*	0.00003*
Sideswipe same direction	0.05104***	−0.03752***	−0.01316***	−0.00033***	−1.54131
Sideswipe opposite direction	−0.06297	0.04564	0.01685	0.00043	0.00005
Motorcycle	−0.96824***	−0.00315	0.42783***	0.43308***	0.11049**
Passenger vehicle	−0.06161***	0.04507***	0.01609***	0.00040***	0.00005***
Cross median	−0.13571***	0.09606***	0.03854***	0.00100***	0.00012***
Run-off-road right	−0.14844***	0.10480***	0.04241***	0.00110***	0.00013***
Run-off-road left	−0.18320***	0.12777***	0.05385***	0.00142***	0.00017***
Age 24 or less	0.01415***	−0.01046***	−0.00359***	−0.41797	−0.418
Age 65 or up	−0.00934**	0.00688**	0.00240**	0.00006**	0.000007**
Female	−0.02231***	0.01641***	0.00574***	0.00014***	0.00002***
Safety device used	0.10238***	−0.07339***	−0.02819***	−0.00072***	−3.38554
Drugs or alcohol used	−0.07173***	0.05186***	0.01933**	0.00049**	0.00006**
Median width <20 Ft	0.00833***	−0.00615***	−0.00212***	−0.24657	−0.24659
Median width >80 Ft	−0.00777**	0.00572**	0.00199**	0.00005**	.000006**
Speed limit 75	0.00835***	−0.00616***	−0.00212***	−0.24751	−0.24753
Right shoulder width <10 Ft	−0.00456	0.00336	0.00117	0.00003	0.000003
Left shoulder width <4 Ft	0.01834***	−0.01355***	−0.00466***	−0.00012***	−0.54237
Percent of trucks >20%	−0.01782***	0.01309***	0.00460***	0.00011***	0.00001***
Level roadway	0.02163***	−0.01587***	−0.00560***	−0.00014***	−0.65657

Note: ***, **, * = significance at 1%, 5%, 10% levels.

frequency models could be used for various future safety studies on the I-10 involving freight or non-freight type crashes.

Segments with either concrete median barriers or cable median barriers tend to experience more freight and non-freight crashes than segments with unprotected medians. This is consistent with past research (*26*) because when a vehicle runs off the road and collides with a median barrier the crash is nearly always reported. However, if a vehicle runs off the road in a rural area with no median barrier it is possible that the incident may not be reported if the vehicle does not collide with another object. While the presence of median barriers may appear to be a safety hazard, it has also been proven in past studies that median barriers are effective in decreasing the severity of run-off-road crashes (*26*). For this study as well, higher crash frequencies being associated with the presence of median barriers is likely a result of median barriers existing in areas that are already prone to high crash frequencies. Interestingly, the presence of median barriers appears to have very similar effects for freight crashes and non-freight crashes.

Segments with low median widths have a similar effect for both freight and non-freight crashes where they correspond with a decrease in crashes which is contradictory to past research (*26*, *27*). This may be due to a long stretch of wide medians with barriers through some of the most heavily traveled segments in Phoenix. Many of the areas with small median widths are in the suburban sections of Phoenix that experience relatively lower AADT compared with central Phoenix. Segments with high median widths are not significant for freight crashes and also indicate a decrease in frequency of non-freight crashes which is in alignment with past research (*27*). These results may be an indicator that the I-10 is adequately designed in terms of median width.

The continuous variables right shoulder width and left shoulder width all indicated that an increase in width decreases the frequency of crashes which is consistent with past studies (*28*). The one exception seen in these results is that the effect of right shoulder width is not significant for freight crashes. This may be because freight vehicles are larger and perhaps more top heavy, the difference between a 10-foot shoulder and a 12-foot shoulder for example may not make a significant difference in crash reductions. Also, there is not much variability in the left shoulder width on the I-10 with the

Table 7. Results for the Non-Freight Random Parameter Ordered Logit Severity Model

Variable	β	Std. error	p-value	Std. dev.	Std. error	p-value
Constant	−1.975	0.155	<.001	3.115	0.026	<.001
Summer months	0.010	0.034	.780	0.188	0.030	<.001
Dust storm	−0.513	0.390	.189	3.536	0.354	<.001
Dark light conditions*	0.332	0.034	<.001			
Collision with concrete barrier	2.252	0.088	<.001	1.240	0.072	<.001
Rollover*	4.505	0.074	<.001			
Jackknife*	−3.032	0.546	<.001			
Single vehicle*	−1.408	0.058	<.001			
Angle	−0.076	0.100	.444	2.079	0.095	<.001
Head on	1.265	0.201	<.001	3.828	0.201	<.001
Sideswipe same direction	−1.580	0.053	<.001	1.249	0.047	<.001
Sideswipe opposite direction	0.326	0.328	.320	0.517	0.336	.124
Motorcycle*	6.956	0.167	<.001			
Passenger vehicle*	1.458	0.131	<.001			
Cross median*	1.889	0.155	<.001			
Run-off-road right	2.016	0.059	<.001	2.102	0.049	<.001
Run-off-road left	2.020	0.056	<.001	0.954	0.042	<.001
Age 24 or less	−0.727	0.033	<.001	0.897	0.027	<.001
Age 65 or up	0.246	0.063	<.001	0.830	0.060	<.001
Female*	0.822	0.030	<.001			
Safety device used*	−2.745	0.063	<.001			
Drugs or alcohol used	1.732	0.127	<.001	4.488	0.144	<.001
Median width <20 Ft*	−0.145	0.036	<.001			
Median width >80 Ft*	0.256	0.061	<.001			
Speed limit 75	−0.573	0.056	<.001	0.906	0.034	<.001
Right shoulder width <10 Ft	−0.040	0.058	.491	0.635	0.045	<.001
Left shoulder width <4 Ft	−0.120	0.058	.038	1.197	0.035	<.001
Percent of trucks >20%	0.302	0.080	<.001	1.145	0.068	<.001
Level roadway*	−0.323	0.116	.006			
Threshold 1	1.920	0.022	<.001			
Threshold 2	6.064	0.057	<.001			
Threshold 3	9.413	0.121	<.001			
Restricted log likelihood (LL)	−35,695.375					
Final LL for fixed model	−33,150.964					
Final LL for RP model	−33,088.906					

*Fixed parameter in RP model.

mean being 10.64 Ft and the standard deviation being 1.93 Ft.

Speed indicators for segments with 65 mph and 75 mph speed limits have the same positive effect for both freight and non-freight crashes and are significant in both models (compared with segments with 45–55 mph speed limits). In previous studies, results for the effect of speed limit on the frequency of total crashes are mixed; however, studies analyzing the severity of crashes often conclude that higher speed limits are often correlated with high fatality rates (*29*). It is interesting that freight crashes are not affected differently than non-freight crashes. It seems intuitive that for the I-10, segments with 65 mph speed limits would have more crashes due to their proximity to urban areas. This result may be due to the conflicts created by speed differentials between freight and passenger vehicles on rural segments.

High degrees of curvature and high percent grade prove to be positive factors for both freight and non-freight type crash frequencies. This result is consistent among most traffic safety studies (*30*). Drivers may enter curves and high grades at unsafe speeds which in turn, leads to higher crash frequencies.

The continuous variable for truck percent is interesting in that its negative effect on crash frequency is not significant for freight crashes but it is for non-freight crashes. This may be an indicator that passenger vehicles are often the ones at fault in truck crashes. However, it could also be another function of vehicle exposure. Low truck percentages are most often observed on urban segments with high passenger vehicle volumes. An Ontario, Canada study found the same result to be true (*9*). The "Phoenix" indicator variable represents the urban area through Phoenix and it has a significant positive effect for both freight and non-freight crashes. This result was

Table 8. Marginal Effects for the Non-Freight RP Ordered Logit Model

Variable	1-no Injury	2-injury	3-injury	4-injury	5-fatal
Summer months	−0.00021	0.00017	0.00003	0.00001	0.00000
Dust storm	0.00868*	−0.00074*	−0.00129*	−0.34517	−0.34518
Dark light conditions	−0.00778***	0.00659***	0.00117***	0.00001***	0.0000006***
Collision with concrete barrier	−0.14684***	0.12128***	0.02515***	0.00040***	.000014***
Rollover	−0.61178***	0.41465***	0.19322***	0.00377***	0.00014***
Jackknife	0.02092***	−0.01779***	−0.00308***	−0.82162	−0.82161
Single vehicle	0.02084***	−0.01769***	−0.00310***	−0.8282	−0.82822
Angle	0.00158	−0.00134	−0.00024	−0.06325	−0.06325
Head on	−0.05131***	0.04314***	0.00804***	0.00013***	0.000005***
Sideswipe same direction	0.02219***	−0.01884***	−0.00330***	−0.88158	−0.88159
Sideswipe opposite direction	−0.00817	0.00691	0.00123	0.00002	0.000001
Motorcycle	−0.93613***	0.17474***	0.71247***	0.04711***	0.00180***
Passenger vehicle	−0.01749***	0.01486***	0.00258***	0.00004***	0.000001***
Cross median	−0.10623***	0.08843***	0.01752***	0.00028***	0.00001***
Run-off-road right	−0.10990***	0.09149***	0.01811***	0.00029***	0.00001***
Run-off-road left	−0.10839***	0.09028***	0.01782***	0.00028***	0.00001***
Age 24 or less	0.01410***	−0.01196***	−0.00211***	−0.56421	−0.56423
Age 65 or up	−0.00587***	0.00497***	0.00088***	0.00001***	0.000001***
Female	−0.01875***	0.01589***	0.00282***	0.00004***	0.000002***
Safety device used	0.22251***	−0.18066***	−0.04115***	−0.00067***	−11.50761
Drugs or alcohol used	−0.08910***	0.07441***	0.01445***	0.00023***	0.000008***
Median width <20 Ft	0.00298***	−0.00253***	−0.00045***	−0.11944	−0.11944
Median width >80 Ft	−0.00611***	0.00518***	0.00092***	0.00001***	0.000001***
Speed limit 75	0.01031***	−0.00875***	−0.00154***	−0.41095	−0.41096
Right shoulder width <10 Ft	0.00084	−0.00072	−0.00013	−0.03385	0.00000
Left shoulder width <4 Ft	0.00247**	−0.00210**	−0.00037**	−0.09893	−0.09894
Percent of trucks >20%	−0.00742***	0.00628***	0.00112***	0.00002***	0.000001***
Level roadway	0.02447***	−0.02067***	−0.00374***	−1.00502	−1.00512

Note: ***, **, * = significance at 1%, 5%, 10% levels.

to be expected: during the data collection process it became evident that a large portion of the sample crashes occurred within the Phoenix area and this is largely the result of high congestion and other potential unobserved characteristics associated with highly populated urban areas.

Ordered Logit Severity Model Results Discussion

One of the most important findings in the severity analysis was that the weather variable, blowing sand and/or dust had a significant effect on the severity of freight-involved crashes as opposed to other weather variables, such as rain, which did not have a significant effect on the severity of freight or non-freight crashes. This finding is of particular significance in Arizona and the southwest USA in general as the stretch of I-10 between Phoenix and Tucson experiences dust storms on a frequent basis, which creates hazardous driving conditions. Dust-storm related crashes are over represented in the freight dataset (i.e., 1.5% of all freight-involved records and 0.3% of non-freight records). This over representation may be due to a more substantial decrease in visibility during dust storms for freight vehicles. Because a freight vehicle's field of vision is higher than a normal passenger vehicle, they may be more at risk of colliding with small vehicles or other objects close to the ground. Trucking companies should make efforts to educate their drivers on what steps to take in the event of a dust storm.

None of the seasons (i.e., winter, summer, etc.) were significant in either severity model, however, summer did display significant variability and therefore was left in the model as a random parameter. In many states with harsh winters, studies have shown that crash severity is often reduced during winter months potentially due to more cautious driving behavior in adverse winter weather conditions (*31*), however this is not the case on the I-10 in Arizona. Another interesting finding in the severity model is that crashes occurring during dark lighting conditions resulted in more severe outcomes for both freight and non-freight crashes. This is likely due to deteriorating visual capabilities and driving behavior at later times in the day and lack of street lighting in rural areas. Dark lighting conditions were also seen to increase injury severity for large truck crashes across the entire interstate system (*32*).

Several indicator variables were created based on the first harmful event recorded for each crash-involved vehicle. While most did not have a statistically significant impact in either severity model, several of them did. For example, crashes with the first harmful event recorded as a rollover resulted in the second highest injury severity outcomes for both freight and non-freight. Collisions with concrete barriers also resulted in more severe injury outcomes. Crashes that had a first harmful event coding of jackknife actually resulted in less severe crashes than other first harmful events. This finding agrees with a study completed in 2014 that found that jackknife crashes were less severe when compared to rollover crashes (*33*).

With respect to collision manner, crashes that involved just a single vehicle were less severe for both freight and non-freight crashes. This is often the case on high speed controlled access highways where there are few hazardous obstructions near the road. Head-on collisions were significant with a positive effect for both freight and non-freight crashes. This is consistent to one past study done in Canada which showed that head-on collisions with large trucks resulted in more severe crashes (*34*).

Injuries were more severe for people in passenger vehicles as opposed to those in freight or other vehicles (a variety of other miscellaneous vehicle body styles such as garbage truck, dump truck, ambulance, etc…) for both freight and non-freight crashes. This result is both intuitive and consistent with past studies (*34*). Crashes involving motorcycles resulted in the most severe results out of any indicator in both the freight and non-freight models. Next, incidents where a vehicle ran off the road left, right, or crossed the median significantly resulted in more severe crashes. The severity of these crashes can be greatly affected by roadway and environmental conditions but in general they tend to result in more severe crashes.

Person-level variables revealed that female motorists were more likely to be injured than other gender identifiers. Also, motorists age 24 or younger were less likely to be injured. These results may be due to physiological differences among gender and age groups. Motorists who had reportedly used drugs or alcohol were more likely to be injured. This result is also common in traffic studies and it has become a large educational campaign across the USA. Another common result was that motorists who used a safety device (i.e., lap belt, shoulder and lap belt, and helmet) were less likely to be injured. These results were significant and had the same effect for both freight and non-freight crashes.

For both freight and non-freight, crashes on segments with low median widths (less than 20 Ft) were less severe while crashes on segments with high median widths (more than 80 Ft) were more severe. Many of the segments with low median widths also had median barriers to prevent head-on collisions and were in urban areas where congestion-related rear-end crashes are common. Interestingly, crashes on segments with 75 mph speed limits were less severe than those with 65 mph or 55 mph speed limits for non-freight, however, this variable was not significant for freight crashes. Narrow right shoulder widths (less than 10 Ft) and narrow left shoulder widths (less than 4 Ft) had significant effects for freight crashes but not non-freight crashes. Narrow right shoulder widths resulted in more severe crashes and narrow left shoulder widths resulted in less severe crashes. Low shoulder widths often led to higher frequencies and higher severity crashes. In this case, the decrease in severity with narrow left shoulder width might again be a matter of urban crashes versus rural crashes. Segments with high percent truck volume experienced more severe outcomes for freight crashes but were not significant for non-freight crashes. Crashes on level roads experienced less severe crashes for both freight and non-freight as compared to crashes on downhill or uphill segments. Interestingly, crashes on curves were not significant in terms of injury severity for either model.

Conclusion

The I-10 corridor through Arizona is of significant importance to goods movement throughout the Southwest and thus its operation is essential to the well-being of the general public and U.S. businesses. Recent studies on the efficiency and safety of the I-10 have revealed that many sections are areas of concern with low safety indexes. Additionally, studies on the safety of freight transport and how it relates to non-freight type transport are few and far between.

Two different statistical methods (RP negative binomial regression and RP ordered logit regression) were used to analyze factors which may lead to high crash frequencies and severe injury outcomes on the I-10 through Arizona. The results of the frequency models revealed that geometric characteristics such as median width, shoulder width and number of lanes were generally less significant for freight-involved crashes than non-freight crashes. Another interesting finding in the frequency models was that both high (i.e., >80 Ft) and low (i.e., <39 Ft) median widths indicated a decrease in crash frequency for non-freight crashes. The results of the severity models revealed that dust-storm crashes were significant and had a positive effect on the severity of freight-involved crashes but they were not significant for non-freight crashes. Head on crashes were not significant for the injury severity of freight-involved crashes but they were significant with a positive effect for the injury severity in non-freight crashes.

In order to improve safety and efficiency on a major freight corridor freeway, agencies should focus on education and enforcement in addition to employing new ITS solutions as opposed to widening shoulders, adding lanes, or changing speed limits. Variable speed limits may help to decrease the severity of dust-storm-related incidents. Dynamic lane control could help reduce the frequency of sideswipe and rear-end crashes in the often congested urban areas of Phoenix and Tucson. Driver-assistance technology for freight vehicles, such as lane departure and collision warning systems, could reduce the frequency and severity of run-off-road, single vehicle, and rollover crashes.

Further studies on the frequency and severity of freight vehicle crashes on either urban or rural areas only, would be beneficial in understanding unobserved spatial factors. For example, fatigue is likely a larger factor in rural areas as opposed to urban areas and the safety impact of wider left shoulder widths might be different in rural areas as opposed to urban areas.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Brendan Russo, Samuel Taylor, and Emmanuel James; data collection: Brendan Russo, Samuel Taylor, and Emmanuel James; analysis and interpretation of results: Brendan Russo and Samuel Taylor; draft manuscript preparation: Brendan Russo and Samuel Taylor. All authors reviewed the results and approved the final version of the manuscript.

References

1. U.S. Department of Transportation. *Economic Impact of Freight*. https://www.rita.dot.gov/bts/programs/freight_-transportation/html/freight_and_growth.html. Accessed July 5, 2017.
2. U.S. Department of Transportation. *Freight Facts and Figures 2015*, 11th ed.https://www.rita.dot.gov/bts/sites/rita.-dot.gov.bts/files/FFF_complete.pdf. Accessed July 5, 2017.
3. Statistics Department National Safety Council. *NSC Motor Vehicle Fatality Estimates*. http://www.nsc.org/NewsDocuments/2017/12-month-estimates.pdf. Accessed July 5, 2017.
4. U.S. Department of Transportation. *Pocket Guide to Large Truck and Bus Statistics*. June 2017. https://ntl.bts.gov/lib/61000/61900/61913/2017-Pocket-Guide-to-Large-Truck-and-Bus-Statistics-Final-508C-01.2.pdf. Accessed July 6, 2017.
5. National Safety Council. *Estimating the Costs of Unintentional Injuries*. March 2015. http://www.nsc.org/NSCDocuments_Corporate/estimating-costs.pdf. Accessed July 5, 2017.
6. I-95 Corridor Coalition. *The Coalition*. http://i95coalition.org/the-coalition-2/. Accessed July 14, 2017.
7. I-10 Corridor Coalition. *Interstate 10 Connects People, Businesses, States and More*. https://i10connects.com/. Accessed July 14, 2017.
8. HDR, ADOT. *I-10 Corridor Profile Study SR 202L to New Mexico State Line*. https://www.azdot.gov/docs/default-source/planning/Corridor-Studies/cps3-i-10e-draft-wp1-(jan-2016).pdf?sfvrsn = 2. Accessed July 3, 2017.
9. Ran, R. *Prediction of Frequencies of Truck-Involved and Non-Truck-Involved Crashes on Roadway Segments in Ontario*. University of Windsor, October 2015.
10. Dong, C., Q. Dong, H. Huang, W. Hu, and S. S. Nambsian. Estimating Factors Contributing to Frequency and Severity of Large Truck-Involved Crashes. *Journal of Transportation Engineering*, Vol. 143, No. 8, 2017. https://ascelibrary.org/doi/10.1061/JTEPBS.0000060
11. AECOM, ADOT. *I-10/SR 85 Corridor Profile Study*. https://www.azdot.gov/docs/default-source/planning/Corridor-Studies/i-10-sr85-executive-summary.pdf?sfvrsn = 2. Accessed July 3, 2017.
12. ESRI 2011. *ArcGIS Desktop: Release 10*. Environmental Systems Research Institute, Redlands, CA, 2011.
13. Arizona Department of Transportation (ADOT). *Arizona's Crash Report Forms Instruction Manual*, 9th ed., pp.24–25, Arizona Department of Transportation, Phoenix, AZ, 2010.
14. Mohammadi, M., V. A. Samaranayake, and G. Bham. Crash Frequency Modeling Using Negative Binomial Models: An Application of Generalized Estimating Equation to Longitudinal Data. *Analytic Methods in Accident Research*, Vol. 2, 2014, pp. 52–69.
15. Jung, S., S. Joo, and O. Cheol. Evaluating the Effects of Supplemental Rest Areas on Freeway Crashes Caused by Drowsy Driving. *Accident Analysis and Prevention*, Vol. 99, 2017, pp. 356–363.
16. Srinivasan, R., and K. Bauer. *Safety Performance Function Development Guide: Developing Jurisdiction Specific SPFs*. Publication FHWA-SA-14-005. FHWA, September 2013.
17. Washington, S., M. Karlaftis, and F. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis*, 2nd ed. Chapman and Hall/CRC, Boca Raton, FL, 2011.
18. Bogue, S., R. Pateli, and L. Balan. A Modified Rank Ordered Logit Model to Analyze Injury Severity of Occupants in Multivehicle Crashes. *Analytic Methods in Accident Research*, Vol. 14, 2017, pp. 22–40.
19. Osman, M., R. Paleti, S. Mishra, and M. M. Golias. Analysis of Injury Severity of Large Truck Crashes in Work Zones. *Accident Analysis & Prevention*, Vol. 97, 2016, pp. 261–273.
20. Monatana Department of Transportation. *Safety and Operational Impacts of Differential Speed Limits on Two-Lane Rural Highways in Montana*. Publication FHWA/MT-16006/8224-001, 2016.
21. Quddus, M. Effects of Geodemographic Profiles of Drivers on Their Injury Severity from Traffic Crashes Using Multilevel Mixed-Effects Ordered Logit Model. *Transportation*

Research Record, Vol. 2514, 2015, pp. 149–157. https://doi.org/10.3141/2514-16
22. Train, K. *Halton Sequences for Mixed Logit*. University of California, Berkeley Department of Economics, July 22, 1999.
23. Zeng, T. Using Halton Sequences in Random Parameters Logit Models. *Journal of Statistical and Economic Methods*, Vol. 5, No. 1, 2016, pp. 59–86.
24. Hensher, D. A., J. M. Rose, and W. H. Greene. *Applied Choice Analysis: A Primer*. Cambridge University Press, New York, 2005.
25. NLOGIT 5. Econometric Software Inc., 2012.
26. Savolainen, P., T. Gates, B. Russo, and J. Kay. Study of High-Tension Cable Barriers on Michigan Roadways MDOT ORBP Project Number: OR10-036, October 2014.
27. The Association of Median Width and Highway Accident Rate. Publication FHWA-RD-93-046, August 1993. https://www.fhwa.dot.gov/publications/research/safety/humanfac/93046/index.cfm. Accessed July 21, 2017.
28. Park, J., and M. Abdel-Aty. Evaluation of Safety Effectiveness of Multiple Cross Sectional Features on Urban Arterials. *Accident Analysis & Prevention*, Vol. 92, 2016, pp. 245–255.
29. Savolainen, P., T. Gates, E. Hacker, A. Davis, S. Frazier, B. Russo, E. Rista, M. Parker, F. Mannering, and W. Schneider. Evaluating the Impacts of Speed Limit Policy Alternatives. *MDOT Research Administration*. Project Number: OR 13-009, July 2014.
30. Gooch, J., V. Gayah, and E. Donnell. Quantifying the Safety Effects of Horizontal Curves on Two-Way, Two-Lane Rural Roads. *Accident Analysis & Prevention*, Vol. 92, 2016, pp. 71–81.
31. Russo, B., P. Savolainen, W. Schneider, and P. Anastasopoulos. Comparison of Factors Affecting Injury Severity in Angle Collisions by Fault Status Using a Random Parameters Bivariate Ordered Probit Model. *Analytic Methods in Accident Research*, Vol. 2, 2014, pp. 21–29.
32. Islam, M., and S. Hernandez. Large Truck-Involved Crashes: Exploratory Injury Severity Analysis. *Journal of Transportation Engineering*, Vol. 139, No. 6, 2013, pp. 596–604.
33. Lemp, J. D., K. M. Kockelman, and A. Unnikrishnan. Analysis of Large Trucks Crash Severity Using Heteroskedastic Ordered Probit Models. *Accident Analysis and Prevention*, Vol. 43, No. 1, 2011, pp. 370–380.
34. Li, X. Analysis of Injury Severity of Drivers Involved in Single-Vehicle and Two-Vehicle Crashes on Ontario Highways. *University of Windsor*, 2014.

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