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. Additionally, during several stakeholder meetings it was determined that insufficient truck parking is becoming a serious issue for road users in the state of Arizona and throughout the country. Therefore, further analysis was completed to better understand the safety effects of parked freight vehicles near highways in the state of Arizona. The results concluded that there were not enough recorded collisions with parked vehicles in the past six years to create accurate statistical models, however, some assumptions about, location, time of day, and collision manner can be made by considering the summary statistics of those crashes. Finally, this study concludes with a brief look at emerging ITS technologies that may serve as effective countermeasures to some of the safety concerns discussed within the frequency, severity, and parked vehicle analyses.

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1.0 Introduction

Goods movement across the US is one of the most significant factors for economic growth in the United States. Between the years of 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 vehicles and commercial vehicles. For example, the I-95 Corridor Coalition involves 15 different states that all work together to share valuable information and a combined 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)*. Just recently, the FHWA listed the I-10 as one of the nations "Corridors of the Future" as depicted in Figure 1.1 (8). Additionally, both the West and East sections of the I-10 in Arizona are considered by the Arizona Department of Transportation (ADOT) as being vital for the overall health of the statewide transportation system *(9)*. However, no in-depth analysis of freight-involved crashes on the entirety of Arizona's portion of the I-10 has been completed.

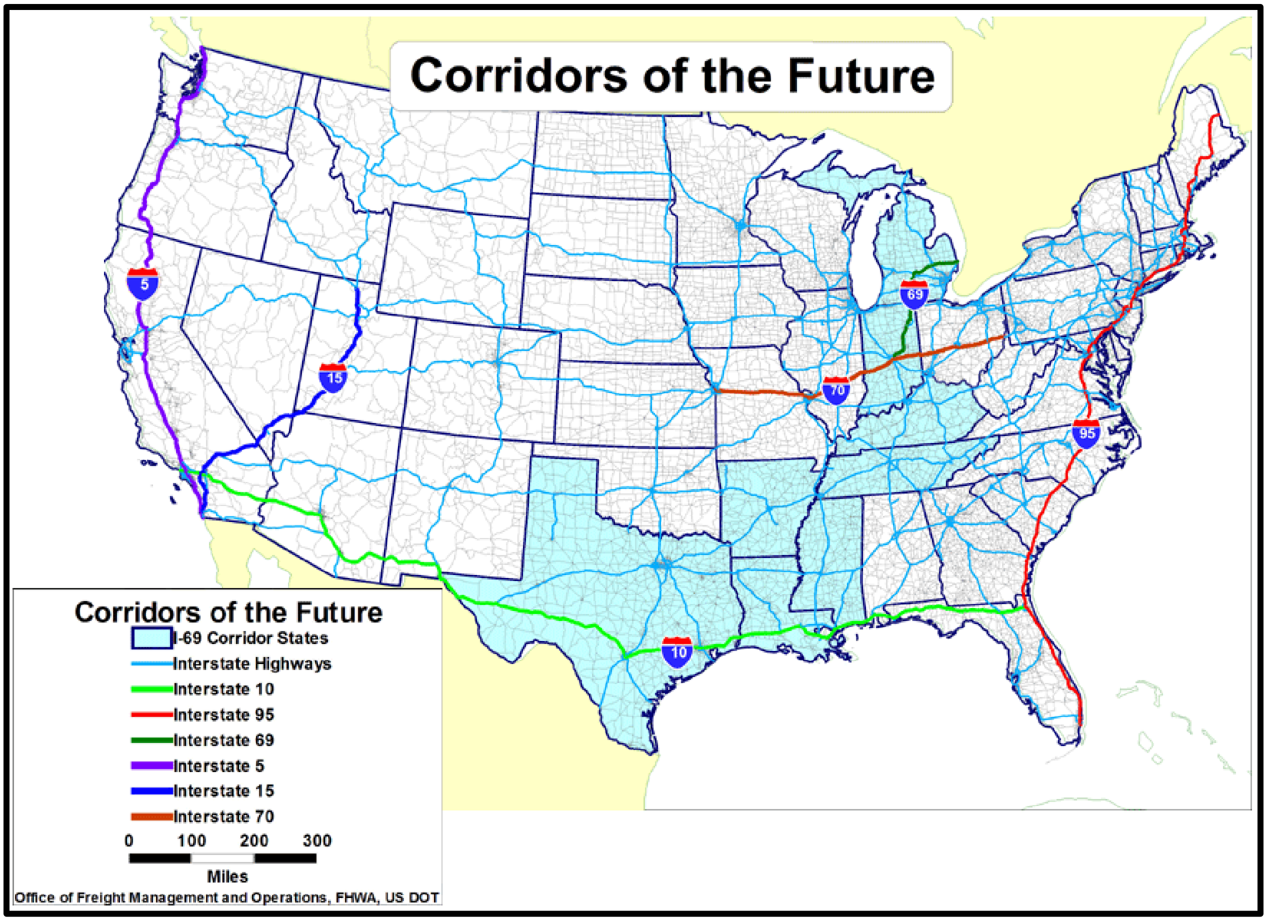

Figure 1.1: FHWA labeled US Corridors of the future

This study utilizes crash data from 2010 through 2015, roadway and traffic characteristics, and two different statistical approaches to analyze factors which may be associated with high crash frequencies severe injuries on the I-10 in Arizona. Additionally, this study takes a detailed look at crashes with parked freight vehicles and considers several Intelligent Transportation Systems (ITS) as countermeasures for the issues presented in the safety analyses. With the entire freeway through Arizona being combined and evaluated as a freight corridor, the findings of this study may be used by public agencies to gain public support for enhancing freight safety and mobility.

1.1 Project Background

With the I-10 corridor coalition gaining traction, transportation professionals at Arizona's three public Universities (NAU, UofA, and ASU) recognized the need for a comprehensive study of freight movement along the I-10 corridor. A joint proposal from all three universities was then submitted to the Arizona Board of Regent's Research Innovation Fund (RIF) and ultimately awarded to facilitate a collaborative research effort to address these concerns.

The overall effort to address freight mobility on the I-10 was eventually narrowed down to Arizona's portion of the I-10 (Outlined in blue in Figure 1.2) and then seven separate project groups were created to address all the issues associated with addressing the problem and managing a project of this magnitude. The research presented in this thesis resulted from work on RIF project 4 – Operational Safety and Efficiency.

Figure 1.2: I-10 Project section through Arizona

During stakeholder meetings over the course of the RIF project, the issue of truck parking, or lack thereof, was found to be a primary concern. Along with the freight crash analyses, this study will look more specifically at crashes involved with parked freight vehicles to determine how many are occurring and what common trends may be associated with these crashes.

As traffic volumes continue to increase across the country and as real-estate becomes more expensive, all members of the RIF project agreed to focus more on studying and recommending intelligent transportation systems or advanced computer technologies as opposed to the more traditional geometric roadway changes. Technology is now advancing at a rate where it has begun to directly influence transportation and this project intends to address all identified issues with state-of-the-art technologies. This study will briefly present four different ITS solutions that have the potential to be effective countermeasures for the safety concerns discussed in the safety analyses.

1.2 Literature Review

Several studies have been completed across the US and Canada that have examined factors affecting either 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 *(10)*. 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 *(10)*.

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 *(11)*. They found that inclement weather conditions increased the frequency and severity of truck-involved crashes *(11)*. 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 *(11)*. 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 *(9, 12)*.

2.0 Crash Frequency Analysis

The first step in this study was to create two negative binomial regression models to estimate the effects that geometric and geographic variables had on the number of expected crashes on existing I-10 highway segments. The first negative binomial model estimates the frequency of only freight-involved crashes based on segment length, traffic volume and a series of other statistically significant explanatory variables. The second negative binomial model is used to estimate the frequency of non-freight involved crashes by using the same explanatory variables as the freight-involved only model. The results from the freight only model is then compared with the results from the non-freight model. This comparison can be useful when planning to reduce the frequency of crashes for all modes of transportation or for one or the other. Essentially, this type of comparative analysis can help agencies make more informed decisions while addressing safety concerns.

2.1 Frequency Analysis 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 through 2015, as well as geometric and traffic volume data from ADOT's Multimodal Planning Division (MPD). A visual of both the Arizona state crash data and the geometric data from the MPD is shown in Figure 2.1

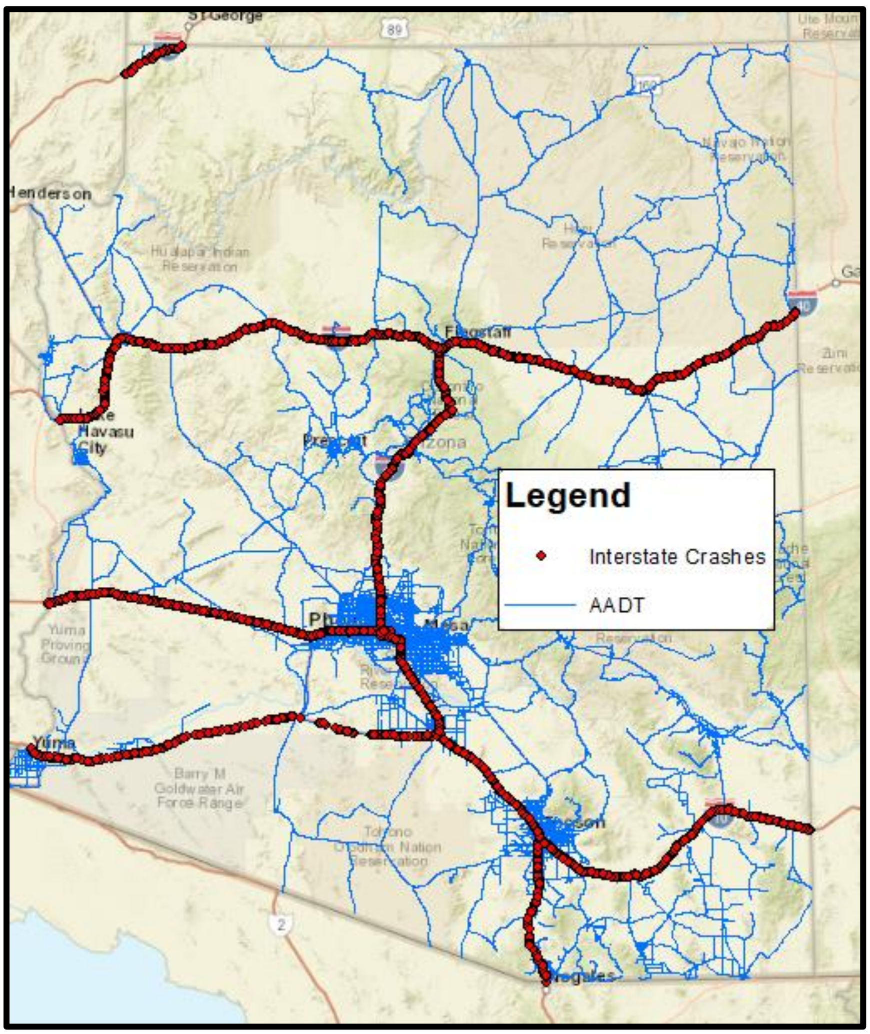

Figure 2.1: Crash data and geometric data combined in ArcMap

These data were then filtered to only include incidents and roadway characteristics on the I-10 through Arizona.

The frequency models both used the same explanatory dataset that consisted of 264 predefined segments with separate segments for the eastbound and westbound directions on the I-10. These segments were previously defined by ADOT's established counting stations and typically only extend from one interchange to the next. 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 listed below to encompass tractor-trailers, box trucks, and auto carriers.

- 55: TRUCK_AC_AUTO_CARRIER
- 82: TRUCK_TK_TRUCK
- 83: TRUCK_TT_TRUCK_TRACTOR
- 84: TRUCK_VN_VAN
- 85: TRUCK_1TVN_VAN_1_TON

Geometric characteristics were then assigned to each segment by intersecting several different geometric layers in ArcMap *(13)* 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 year to year. Ultimately, the 'freight-involved' dataset consisted of 5,695 unique crashes while the 'non-freight' data set (which included all non-freight crashes on the I-10 over the study period) consisted of 30,037 unique 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. Descriptive statistics for variables utilized in the frequency models are presented in Table 2.1.

Table 2.1: 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 feet*	0.27	0.44	0.00	1.00
Median Width 40-79 feet*	0.58	0.49	0.00	1.00
Median Width > 80 feet*	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[1]	3.60	3.65	0.00	24.0
Non-Freight Crashes[2]	19.60	26.53	0.00	243
*Binary indicator variable (i.e. 0 or 1) [1]Dependent variable for the freight-involved crashes only model [2]Dependent variable for the non-freight model				

One interesting dynamic that needed to be controlled for and understood when running these models and reading the results was that the I-10 in Arizona passes directly through Arizona's two largest metropolitan areas in Phoenix and Tucson. Because of this, many of the explanatory variables used in the frequency and the severity analyses had large variations associated with "urban" vs. "rural" characteristics. In order to control for this distinction, a Phoenix indicator variable was used in the model and is depicted in Table 2.1. Figure 2.2 and 2.3 also illustrate this dynamic as a vehicle drives eastbound from the California border to the New Mexico border. Traffic volumes (AADT) have high spikes in the heavily populated urban areas of Phoenix and Tucson and the segment lengths have low spikes in the Phoenix and Tucson areas.

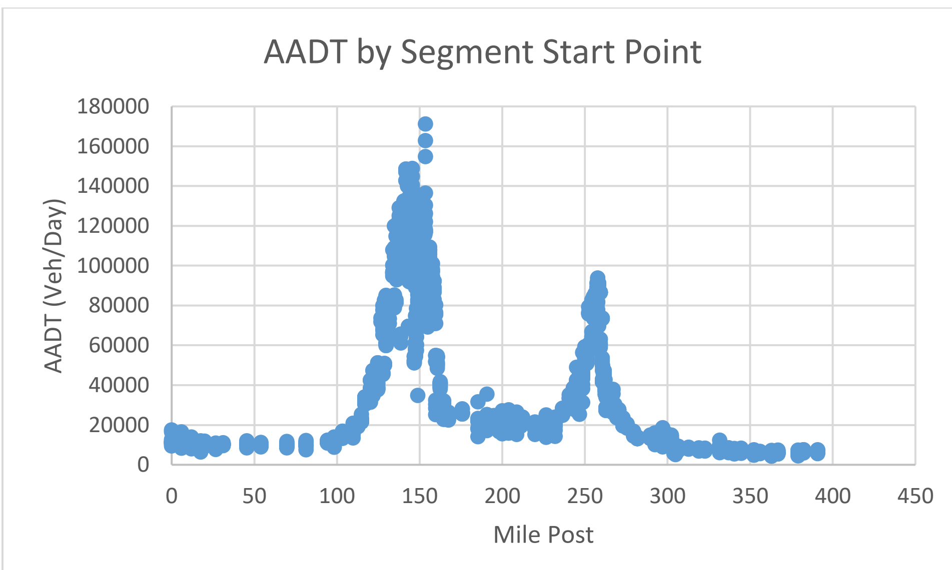

Figure 2.2: AADT by increasing mile post (CA border to NM border)

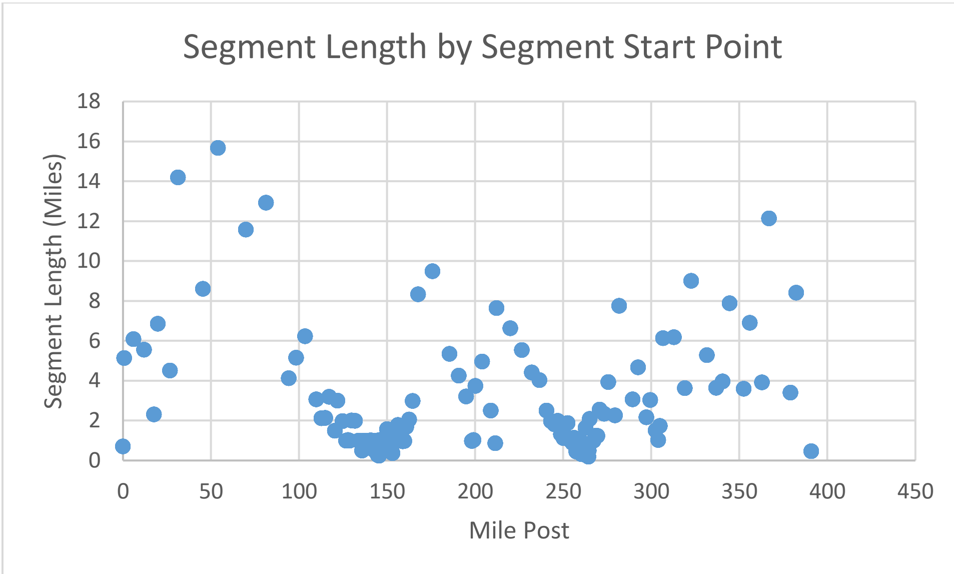

Figure 2.3: Segment length by increasing mile post (CA border to NM border)

It should also be noted that other geometric variables change as well based on whether it is a rural or urban segment. For example, typically median and shoulder widths are smaller in urban areas than rural areas. Speed limits are often lower in urban areas and higher in rural areas. The number of lanes are also often higher in urban areas and lower in rural areas.

2.2 Frequency Analysis Methodology

Using a negative binomial model for crash frequency predictions has been proven to be effective in past studies *(11, 14, 15)*, and it is one of the most popular methods for the development of Safety Performance Functions (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)*:

$$\lambda_i = EXP(\beta_0 + \beta_1 X_1 + \beta_i X_i + \varepsilon_i) \tag{1}$$

Where:

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

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.

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 *(18, 19)*. 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:

$$\beta_i = \beta + \omega_n \tag{3}$$

where:

β_i: estimable parameter

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

2.3 Frequency Analysis Results

The results of the random parameter negative binomial models (frequency models) are presented in Table 2.2. 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 in the results, the natural log of AADT was used instead of AADT itself.

It should be noted that the frequency models included both continuous and binary indicator variables, therefore, the magnitude of the beta values does not directly represent magnitudes of expected change in crash frequency. Of particular interest is the direction or sign for each beta value which indicate the general effect of each variable (i.e. increasing or decreasing crash frequency).

Table 2.2: Results for the Random Parameter Negative Binomial Frequency Models

Freight-Involved Model	**β**	**Std. Error**	**P-Value**	**Std. Dev.**	**Std. Error**	**P-Value**
Intercept	-7.138	0.852	<0.001	0.113	0.017	<0.001
Segment Length*	0.184	0.008	<0.001			
Ln(AADT)	0.704	0.073	<0.001	0.014	0.002	<0.001
Cable Barrier*	0.180	0.102	0.076			
Concrete Barrier	0.237	0.089	0.008	0.277	0.029	<0.001
Median Width < 39 (ft.)*	-0.181	0.058	0.002			
Median Width > 80 (ft.)*	0.034	0.061	0.575			
Right Shoulder (ft.)*	0.002	0.011	0.853			
Left Shoulder (ft.)	-0.032	0.009	0.001	0.007	0.002	0.001
3 or 4 Lanes*	0.071	0.076	0.347			
5 or 6 Lanes	-0.140	0.101	0.167	0.324	0.035	<0.001
Speed Limit 65*	0.334	0.086	<0.001			
Speed Limit 75*	0.490	0.088	<0.001			
Degree of Curvature*	0.222	0.098	0.023			
Percent Grade	0.121	0.038	0.002	0.137	0.019	<0.001
Truck Percent*	-0.006	0.004	0.166			
Phoenix Indicator*	0.437	0.095	<0.001			
Over-Dispersion**	0.117	1.101	<0.001			
Non-Freight Model	**β**	**Std. Error**	**P-Value**	**Std. Dev.**	**Std. Error**	**P-Value**
Intercept	-10.663	0.608	<0.001	0.167	0.012	<0.001
Segment Length*	0.187	0.006	<0.001			
Ln(AADT)	1.187	0.052	<0.001	0.020	0.001	<0.001
Cable Barrier*	0.190	0.069	0.006			
Concrete Barrier	0.306	0.061	<0.001	0.250	0.020	<0.001
Median Width < 39 (ft.)*	-0.229	0.041	<0.001			
Median Width > 80 (ft.)*	-0.267	0.043	<0.001			
Right Shoulder (ft.)*	-0.024	0.008	0.004			
Left Shoulder (ft.)	-0.016	0.007	0.018	0.007	0.001	<0.001
3 or 4 Lanes*	-0.132	0.052	0.011			
5 or 6 Lanes	-0.312	0.071	<0.001	0.266	0.025	<0.001
Speed Limit 65*	0.795	0.059	<0.001			
Speed Limit 75*	1.002	0.061	<0.001			
Degree of Curvature*	0.417	0.068	<0.001			
Percent Grade	0.133	0.026	<0.001	0.222	0.013	<0.001
Truck Percent*	-0.018	0.003	<0.001			
Phoenix Indicator*	0.219	0.065	0.001			
Over-Dispersion**	0.128	0.445	<0.001			
*Fixed Parameter in RP Model						
**Over-dispersion parameter for the negative binomial model framework						

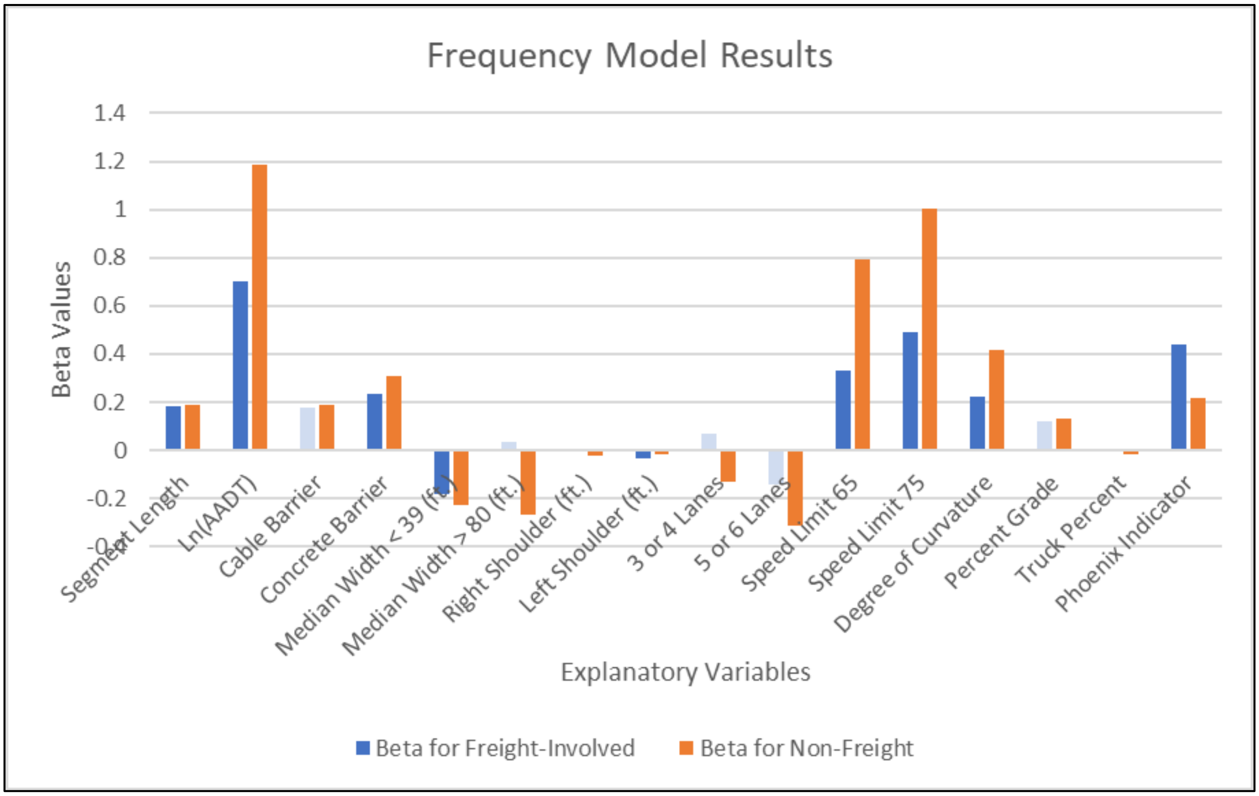

Figure 2.4: Visual representation of resulting Beta values in the frequency models

Figure 2.4 provides a visual for comparison of the effects that each variable have in both the freight and non-freight models. The faded bars are representative of a statistically non-significant variables while the bold color bars are statistically significant. It is evident just by looking at significance that the same geometric characteristics appear to have a smaller impact on the frequency of freight-involved crashes. This observation might be a result of less observations for freight-involved crashes or it might be that freight vehicles are affected less by roadway geometry.

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 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 *(20)* 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 *(21)*. 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 *(20, 21)*. This may be due to a long stretch of wide medians with barriers through some of the most heavily travelled 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

(21). 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 *(22)*. 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 mean being 10.64 feet and the standard deviation being 1.93 feet.

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 *(23)*. 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 frequency. This result is consistent among most traffic safety studies *(24)*. 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 *(10)*. The “Phoenix” indicator variable represents the urban area through Phoenix and it has a significant positive affect for both freight and non-freight crashes. This result was 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.

3.0 Crash Severity Analysis

As a second, and equally important part of this safety analysis, the injury severity outcomes of freight involved and non-freight crashes on the I-10 were estimated using two ordered logit models. Just like the frequency analysis, each of the two severity models included the same explanatory variables and a comparison between freight and non-freight can be made when looking at the effect each variable has on injury severity outcomes. Injury severity analyses like this one may be used by agencies to make informed decisions on limiting the occurrence of severe injury crashes. Additionally, the ordered logit model can consider incident, unit, and person related factors as explanatory variables that the frequency model could not.

3.1 Severity Analysis Data Description

Unlike the frequency analysis, the severity analysis utilizes two entirely separate data sets, one for freight-involved and one for non-freight. These data sets included all persons as unique observations, for example, if three people were involved in one crash, this data set would consider all three people as separate observations with unique person characteristics. 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 data set 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 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 *(25)*:

- **5-Injury: Fatal Injury (K-injury)** - Any injury that results in death within a 30 - 24 hour (i.e. 30 day) time period after the crash occurred.
- **4-Injury: Incapacitating Injury (A-injury)** - Any injury, other than a fatal injury, which prevents the injured person from walking, driving or normally continuing the activities the person was capable of performing before the injury occurred. Often defined as “needing help from the scene.” Includes: severe lacerations, broken or distorted limbs, skull or chest injuries, abdominal injuries, unconsciousness when taken from the crash scene.
- **3-Injury: Non-Incapacitating Injury (B-injury)** - Any injury, other than a fatal injury or an incapacitating injury, which is evident to observers at the scene of the crash in which the injury occurred. Examples: contusions (bruises), laceration, bloody nose, lump on head, or abrasions.
- **2-Injury: Possible Injury (C-injury)** - Complaint of pain without visible injury. Includes – momentary unconsciousness, claim of injuries not evident, limping, complaint of pain, nausea or hysteria.
- **1-No Injury (O – No injury)** - No complaint or treatment was required by the person.

In the two severity data sets, 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 data set are presented in Table 3.1 and summary statistics for the non-freight severity data set are presented in Table 3.2. Again, note that all variables contained in Tables 3.1 and 3.2 are binary indicator variables.

Table 3.1: 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 < 20ft	2,357 (87%)	191 (7%)	125 (5%)	15 (1%)	6 (<1%)	**2,694**
Median Width > 80ft	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 < 10ft	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 < 4ft	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**

Table 3.2: 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 < 20ft	13,416 (85%)	1,335 (8%)	925 (6%)	123 (<1%)	26 (<1%)	**15,825**
Median Width > 80ft	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 < 10ft	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 < 4ft	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**

3.2 Severity Analysis Methodology

Several past studies have successfully utilized discrete outcome models such as the ordered logit model in past traffic safety studies *(26, 27)*. 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)*.

$$Z = \beta X + \varepsilon \tag{3}$$

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:

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

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)*:

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

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*

Figure 3.1 below shows an example probability distribution with labeled severity thresholds. Figure 3.2 then shows how all the thresholds would change when a beta value increases

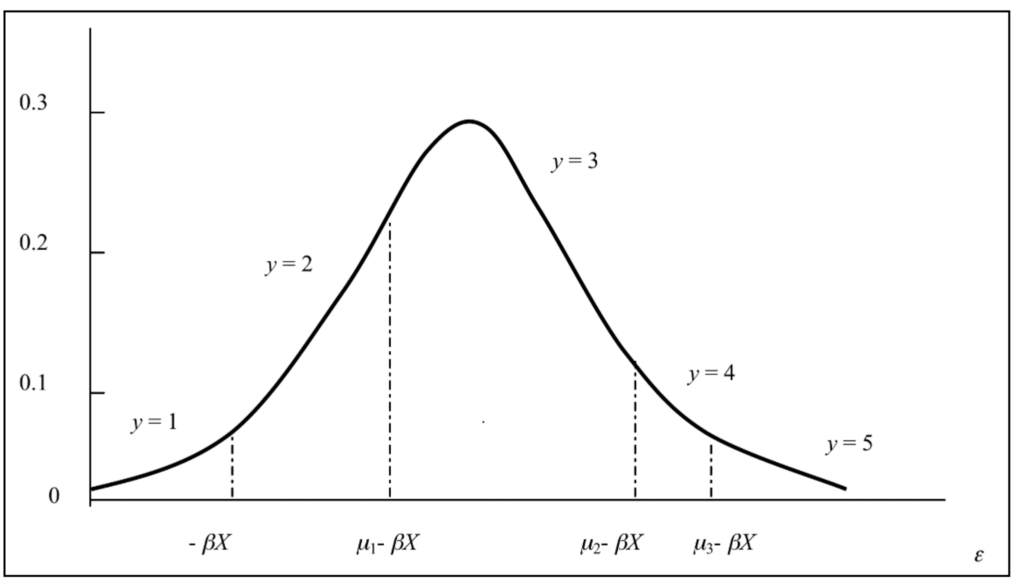

Figure 3.1: Example ordered logit model with labeled thresholds *(18)*

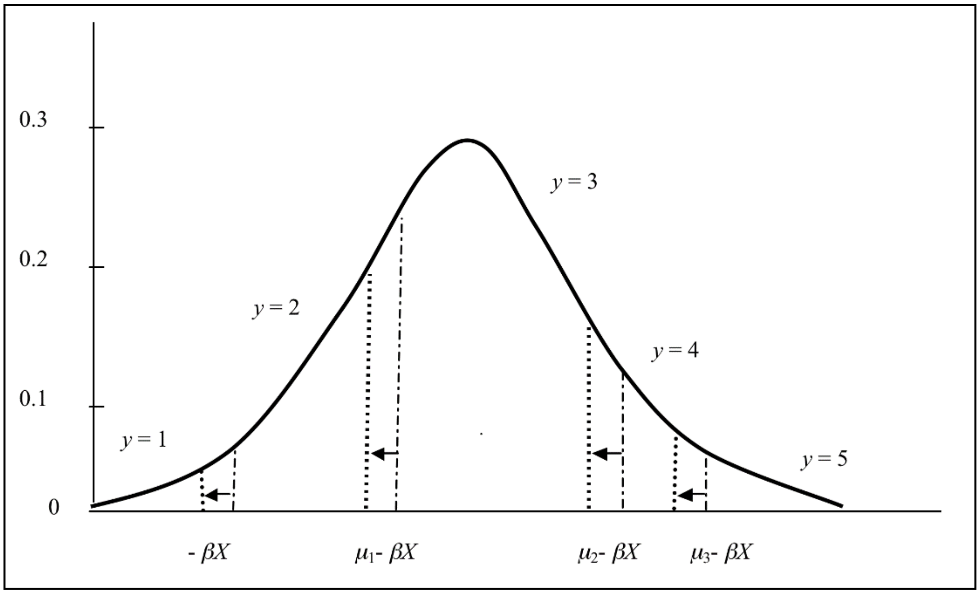

Figure 3.2: Example ordered logit model with shifting thresholds as the beta value increases *(18)*

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 data set. Further information regarding panel data is provided elsewhere *(17)*.

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 *(28, 29, 30)*. 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 calculation of marginal effects is provided elsewhere *(17)*. All models in this study were developed using the statistical software NLOGIT 5 *(31)*.

3.3 Severity Analysis Results

The results of the random parameter ordered logit models (severity models) are presented in Tables 3.3 and 3.5. 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 parameters estimates.

The results of the marginal effects estimation for both severity models are presented in Tables 3.4 and 3.6. While the marginal effects of several variables are small, when the costs of severe motor vehicle crashes *(6)* 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.

Table 3.3 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	<0.001	1.956	0.045	<0.001
Summer Months	-0.135	0.083	0.101	1.227	0.071	<0.001
Dust Storm	1.113	0.267	<0.001	2.282	0.258	<0.001
Dark Light Conditions*	0.467	0.072	<0.001			
Collision with Concrete Barrier	2.097	0.467	<0.001	3.575	0.482	<0.001
Rollover*	3.703	0.226	<0.001			
Jackknife*	-2.120	0.914	0.020			
Single Vehicle*	-1.942	0.186	<0.001			
Angle	-0.979	0.192	<0.001	3.282	0.179	<0.001
Head On	0.994	0.322	0.002	2.694	0.329	<0.001
Sideswipe Same Direction	-2.064	0.089	<0.001	0.823	0.067	<0.001
Sideswipe Opposite Direction	1.286	0.504	0.011	1.381	0.544	0.011
Motorcycle*	8.796	0.504	<0.001			
Passenger Vehicle*	1.949	0.081	<0.001			
Cross Median*	1.972	0.305	<0.001			
Run-Off-Road Right	2.164	0.128	<0.001	2.149	0.112	<0.001
Run-Off-Road Left	2.426	0.119	<0.001	1.264	0.094	<0.001
Age 24 or Less	-0.645	0.084	<0.001	1.469	0.074	<0.001
Age 65 or Up	0.317	0.134	0.018	1.429	0.120	<0.001
Female*	0.740	0.068	<0.001			
Safety Device Used*	-1.769	0.110	<0.001			
Drugs or Alcohol Used	1.395	0.302	<0.001	4.979	0.382	<0.001
Median Width < 20ft*	-0.356	0.093	<0.001			
Median Width > 80ft*	0.273	0.116	0.019			
Speed Limit 75	-0.345	0.112	0.002	1.542	0.064	<0.001
Right Shoulder Width < 10ft	0.167	0.111	0.133	0.263	0.078	0.001
Left Shoulder Width < 4ft	-0.836	0.123	<0.001	1.524	0.069	<0.001
Percent of Trucks > 20%	0.552	0.126	<0.001	0.887	0.104	<0.001
Level Roadway*	-0.323	0.116	0.006			
Threshold 1	1.379	0.039	<0.001			
Threshold 2	5.003	0.110	<0.001			
Threshold 3	7.264	0.198	<0.001			
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						

Table 3.4: 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 < 20ft	0.00833***	-0.00615***	-0.00212***	-0.24657	-0.24659
Median Width > 80ft	-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 < 10ft	-0.00456	0.00336	0.00117	0.00003	0.000003
Left Shoulder Width < 4ft	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% level.

Table 3.5: 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	<0.001	3.115	0.026	<0.001
Summer Months	0.010	0.034	0.780	0.188	0.030	<0.001
Dust Storm	-0.513	0.390	0.189	3.536	0.354	<0.001
Dark Light Conditions*	0.332	0.034	<0.001			
Collision with Concrete Barrier	2.252	0.088	<0.001	1.240	0.072	<0.001
Rollover*	4.505	0.074	<0.001			
Jackknife*	-3.032	0.546	<0.001			
Single Vehicle*	-1.408	0.058	<0.001			
Angle	-0.076	0.100	0.444	2.079	0.095	<0.001
Head On	1.265	0.201	<0.001	3.828	0.201	<0.001
Sideswipe Same Direction	-1.580	0.053	<0.001	1.249	0.047	<0.001
Sideswipe Opposite Direction	0.326	0.328	0.320	0.517	0.336	0.124
Motorcycle*	6.956	0.167	<0.001			
Passenger Vehicle*	1.458	0.131	<0.001			
Cross Median*	1.889	0.155	<0.001			
Run-Off-Road Right	2.016	0.059	<0.001	2.102	0.049	<0.001
Run-Off-Road Left	2.020	0.056	<0.001	0.954	0.042	<0.001
Age 24 or Less	-0.727	0.033	<0.001	0.897	0.027	<0.001
Age 65 or Up	0.246	0.063	<0.001	0.830	0.060	<0.001
Female*	0.822	0.030	<0.001			
Safety Device Used*	-2.745	0.063	<0.001			
Drugs or Alcohol Used	1.732	0.127	<0.001	4.488	0.144	<0.001
Median Width < 20ft*	-0.145	0.036	<0.001			
Median Width > 80ft*	0.256	0.061	<0.001			
Speed Limit 75	-0.573	0.056	<0.001	0.906	0.034	<0.001
Right Shoulder Width < 10ft	-0.040	0.058	0.491	0.635	0.045	<0.001
Left Shoulder Width < 4ft	-0.120	0.058	0.038	1.197	0.035	<0.001
Percent of Trucks > 20%	0.302	0.080	<0.001	1.145	0.068	<0.001
Level Roadway*	-0.323	0.116	0.006			
Threshold 1	1.920	0.022	<0.001			
Threshold 2	6.064	0.057	<0.001			
Threshold 3	9.413	0.121	<0.001			
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						

Table 3.6: 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 < 20ft	0.00298***	-0.00253***	-0.00045***	-0.11944	-0.11944
Median Width > 80ft	-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 < 10ft	0.00084	-0.00072	-0.00013	-0.03385	0.00000
Left Shoulder Width < 4ft	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% level.

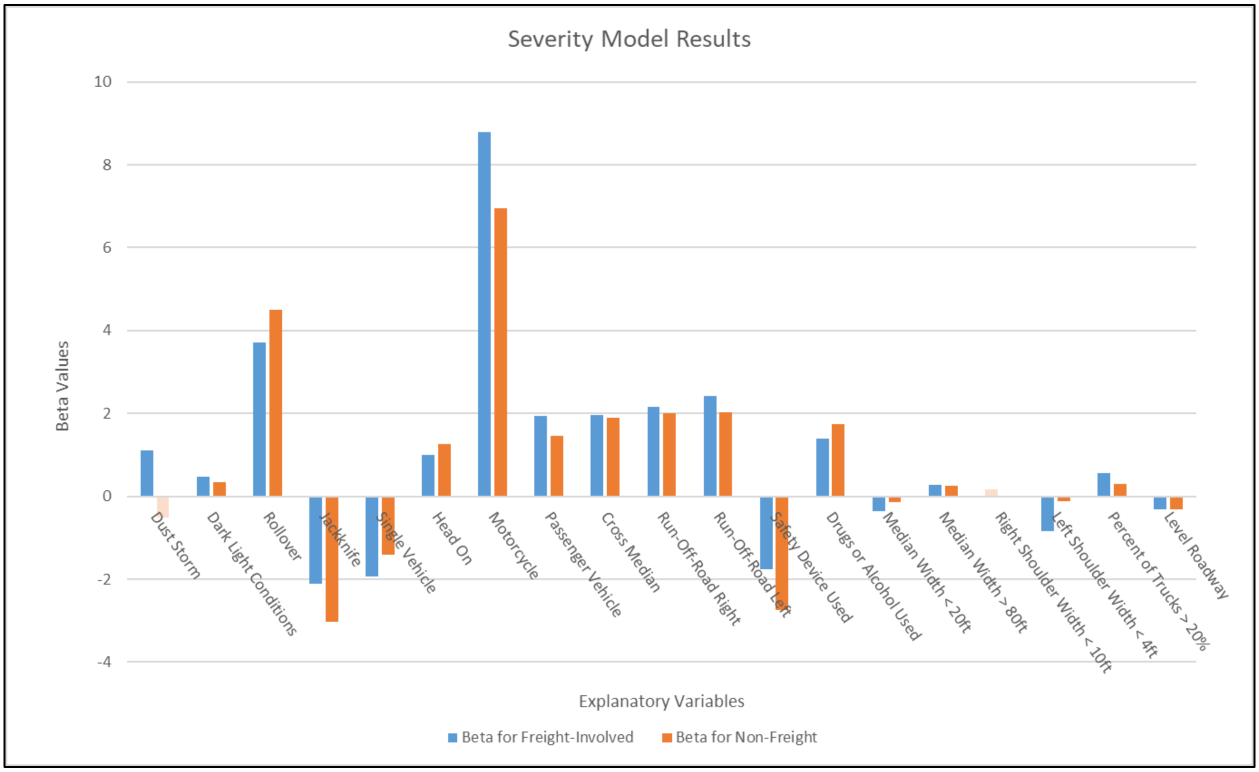

Figure 3.3: Visual representation of resulting Beta values in the severity models

Some important observations can be made just by looking at trends in Figure 3.3. For example, there are more significant freight-involved variables in the severity analysis than the frequency analysis (Figure 2.3). These results indicate that geometric variables play a more significant role in crash frequency than crash severity outcomes.

Another important result that should be noted is that the geometric variables overall had smaller effects or beta value magnitudes than the unit and person variables. This could indicate that geometric factors have a smaller impact on injury severity outcomes or that more precise geometric date is required for more accurate results. Unlike the frequency models, the magnitude of the beta values can be considered in these results because all explanatory variables have been converted to binary indicator variables.

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 US 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 for 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. Figure 3.4 below is a graph depicting the injury severity distribution for dust storm related crashes. These summary statistics support the findings of the model as freight-involved crashes experienced higher injury percentages than non-freight crashes.

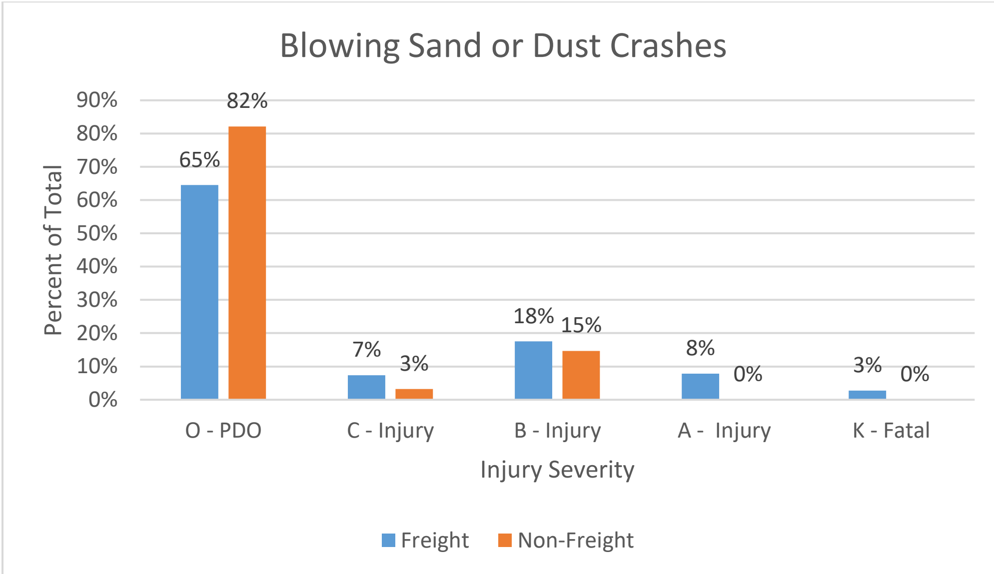

Figure 3.4: Injury severity distribution for blowing sand and dust related crashes

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 *(32)*, 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. *(33)* Figure 3.5 shows how injury percentages between freight and non-freight crashes in dark light conditions were very similar and therefore, dark light conditions do not appear to affect the severity of freight-involved crashes any differently than non-freight crashes.

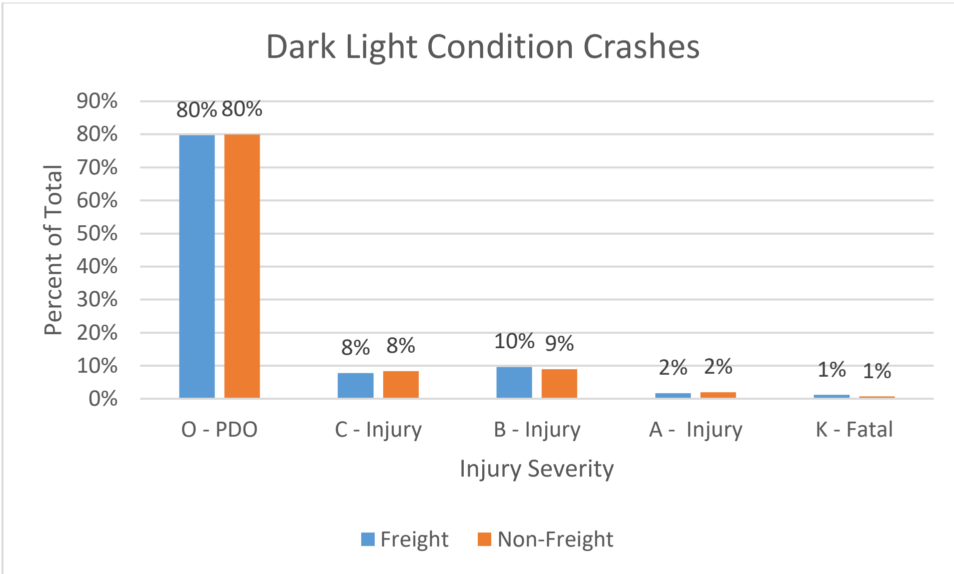

Figure 3.5: Injury severity distribution for dark light related crashes

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 *(34)*. Figure 3.6 displays the injury severity distribution for rollover crashes, note that severe injury percentages are much higher than many of the other variables shown in the other figures in this section. This result corresponds with the marginal effects results in Tables 3.4 and 3.6 for roll over crashes. The marginal effects show a high probability increase in B injuries for roll over crashes.

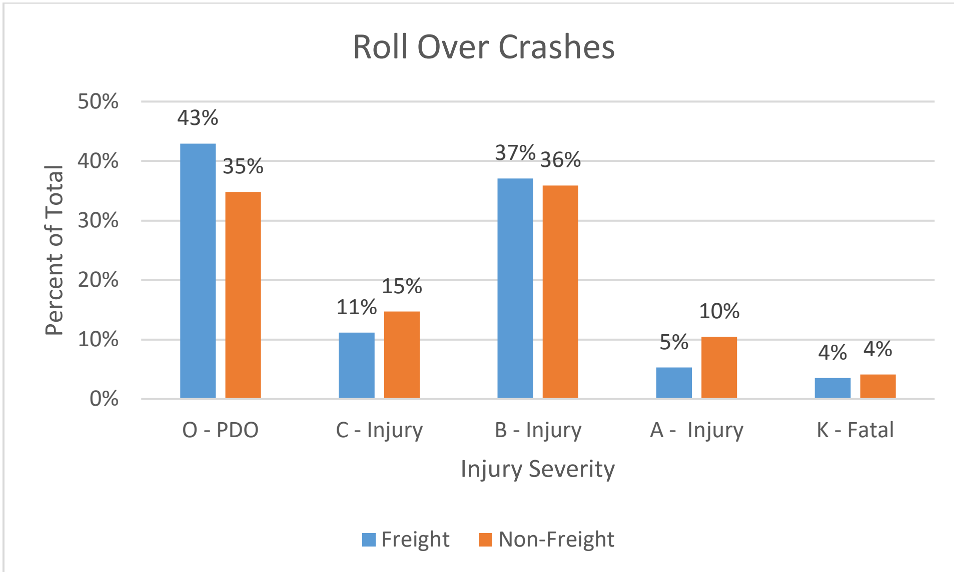

Figure 3.6: Injury severity distribution for roll over crashes

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 *(35)*. Figure 3.7 displays the injury severity distribution for single vehicle crashes which had negative beta values for both freight and non-freight crashes. While the injury percentages for B-injuries are relatively high, the other injury severity levels are low. This is expected because single vehicle crashes on highways have lower probabilities of severe injury outcomes.

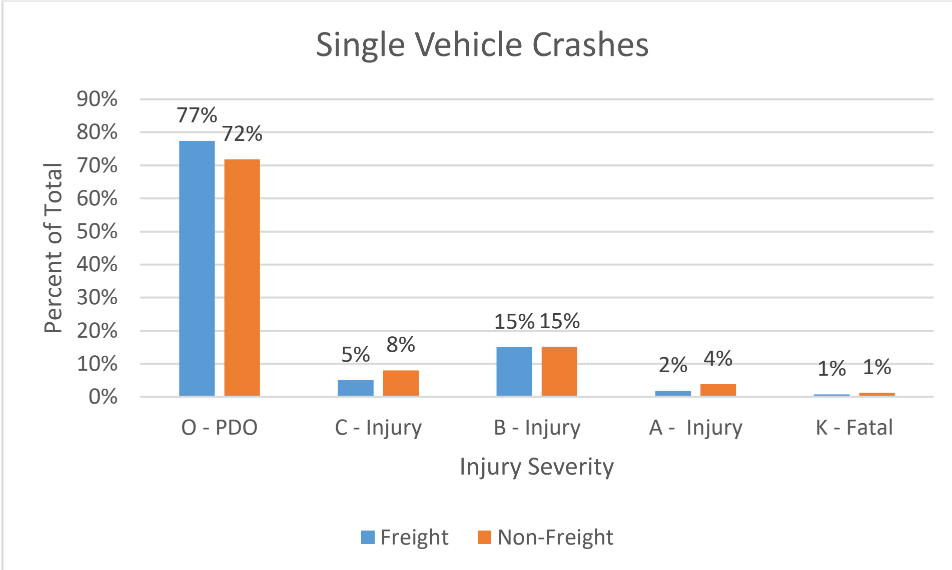

Figure 3.7: Injury severity distribution for single vehicle crashes

Injuries were more severe for people in passenger vehicles as opposed to those in freight vehicles 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 *(36)*. 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. Figure 3.8 presents the injury severity distribution for freight-involved crashes only but compares freight occupants to passenger vehicle occupants. As one would expect, passenger vehicle occupants have higher injury percentages and positive beta values in the model results.

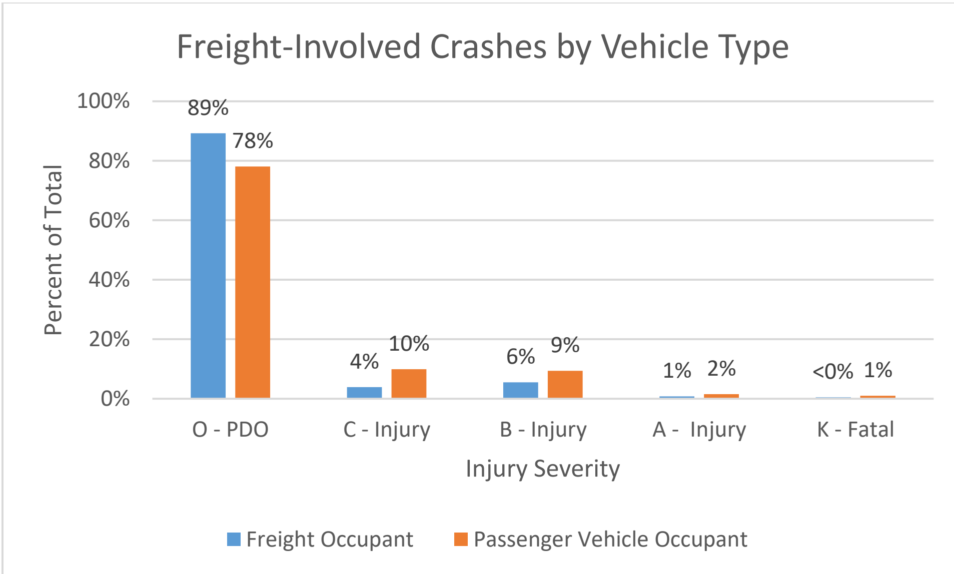

Figure 3.8: Injury severity distribution in freight-involved crashes by vehicle type

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 US. It may be possible to address this common concern strengthening DUI laws and using more check points. 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. Note that there is a large difference in injury severity distributions between figures 3.9 and 3.10. Like most traffic safety studies, this one concludes that seatbelts can save lives and drugs and alcohol can take lives.

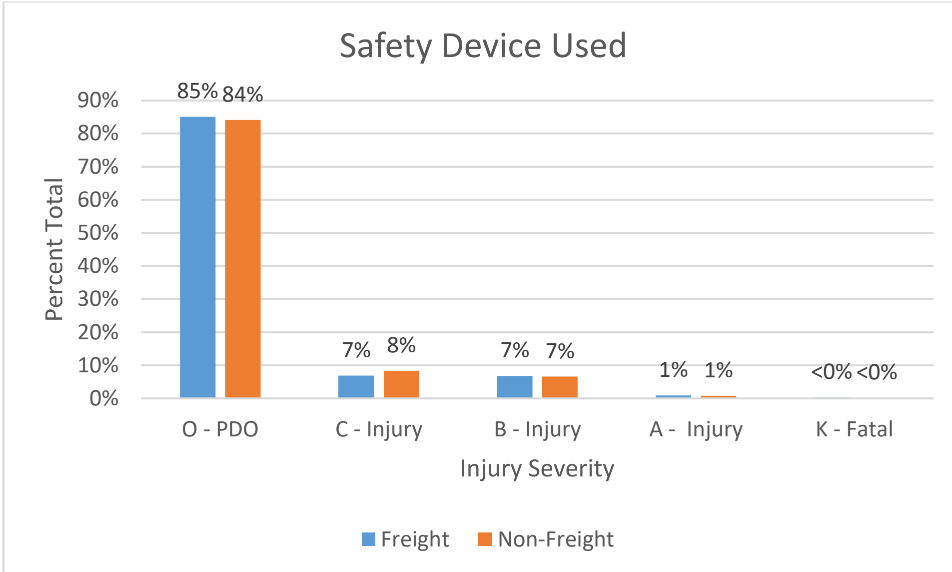

Figure 3.9: Injury severity distribution for occupants that used a safety device

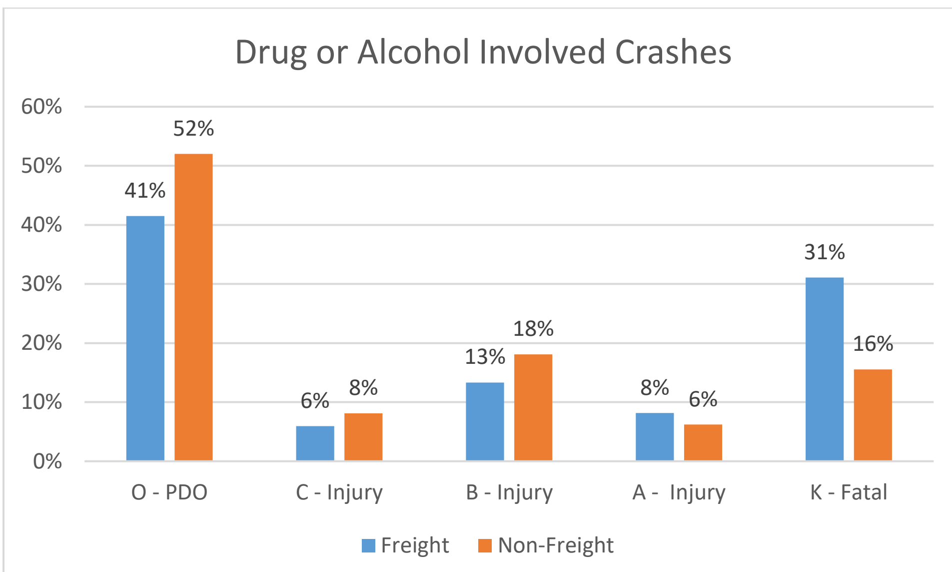

Figure 3.10: Injury severity distribution for occupants that used drugs or alcohol

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 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.

4.0 Parked Vehicle Crash Analysis

Over the course of several collaborative meetings between the three universities and the project stakeholders it has become clear that an increasing lack of truck parking along US interstates has become one of this projects primary concerns. This safety hazard has become a greater concern in recent years due to the newly required electronic data loggers which require drivers to stop after driving for a certain amount of hours. In many cases, any parked vehicle near to a controlled access highway can be considered a safety hazard and can negatively affect the highway's efficiency during high volume hours. This section will analyze illegal truck parking instances near Arizona interstates, state routes, and US highways from a safety perspective to determine if and how this issue is affecting the performance of highways in Arizona and the US.

4.1 Parked Vehicle Literature Review

Overall, very few studies have been successful at estimating the effects that crash and/or roadway characteristics have on the frequency or severity of parked vehicle crashes on highways. More often than not, the total number of observable parked vehicle crashes is too low to create an accurate prediction model.

In 2003, a study was commissioned by the Virginia DOT to investigate crashes involving trucks and other large vehicles stopped on the roadway or shoulder and struck in the rear *(36)*. This study utilized five years of crash data in the state of Virginia and presented descriptive statistics. They observed that there were only a few crashes where a large truck stopped on the roadway or shoulder struck in the rear by a passenger vehicle. They also noted that rear-end crashes in which the leading vehicle was stopped were more numerous, but single-vehicle roadway departure crashes into parked vehicles were more severe. Environmental, roadway, and surface conditions had little influence. They concluded that the major contributing factor was driver inattention. They also mentioned that it is likely that large trucks are more conspicuous than other stopped vehicles because of their size, unique profile, and requirements for reflectorized tape *(36)*.

In 2017, another study was completed in China that used a multinomial logit model and three years of crash data near Beijing to predict the likelihood for severe-injury-rear-end crashes involving trucks *(37)*. This study concluded that driver's age, vehicle weight difference, visibility condition, and lane number increased likelihood for severe injury rear-end crash and that night time, weekdays, tourist, and passenger vehicles as rear vehicles increase the likelihood of rear drivers being fatal *(37)*.

Another study was completed in the UK in 2002 that analyzed “looked but failed to see” accidents involving parked police vehicles *(38)*. The study showed six, 2 min videos to participants They concluded that all participants responded to the parked police car as a hazard, regardless of its parked orientation. Experience drivers responded to echelon-parked vehicles faster than inline parked vehicles. Drivers would have 6 seconds to take action to avoid a collision with the parked car. They did not observe any significant interaction between orientation and attention. Participants who had higher logical reasoning scores took longer to respond to the parked car *(38)*.

A study in 2009 applied the ordered probit model to injury severity in truck-passenger car rear-end collisions *(39)*. The authors concluded that the variables that increase passenger vehicle occupant injury severity include darkness; high speed differentials; high speed limits; grades, especially when they are wet; being in a car struck to the rear (as opposed to being in a car striking a truck to the rear); driving while drunk; and being female. Variables decreasing severity include snowy or icy roads, congested roads, being in a station wagon struck to the rear (as opposed to a sedan), and using a child restraint *(39)*.

4.2 Data Description

The data for the parked vehicle analysis was acquired by first filtering all I-10 crashes from the 2010 – 2015 data base to those that had a first harmful event of “Collision with parked vehicle”. However, concerns arose over the number of observations so the scope was widened to include all such crashes with any event sequence of collision with parked vehicle and on any interstate, US route, or state route. This search yielded a large number of parked vehicle related crashes however, the purpose of this study was to look at collisions with parked freight vehicles so these state-wide crashes needed to be filter to only include such crashes. This was done by only considering crashes with freight vehicles that had an estimated speed of 0 or unknown. This search concluded with a total of 185 such crashes and their location and severity can be seen below in Figure 4.1

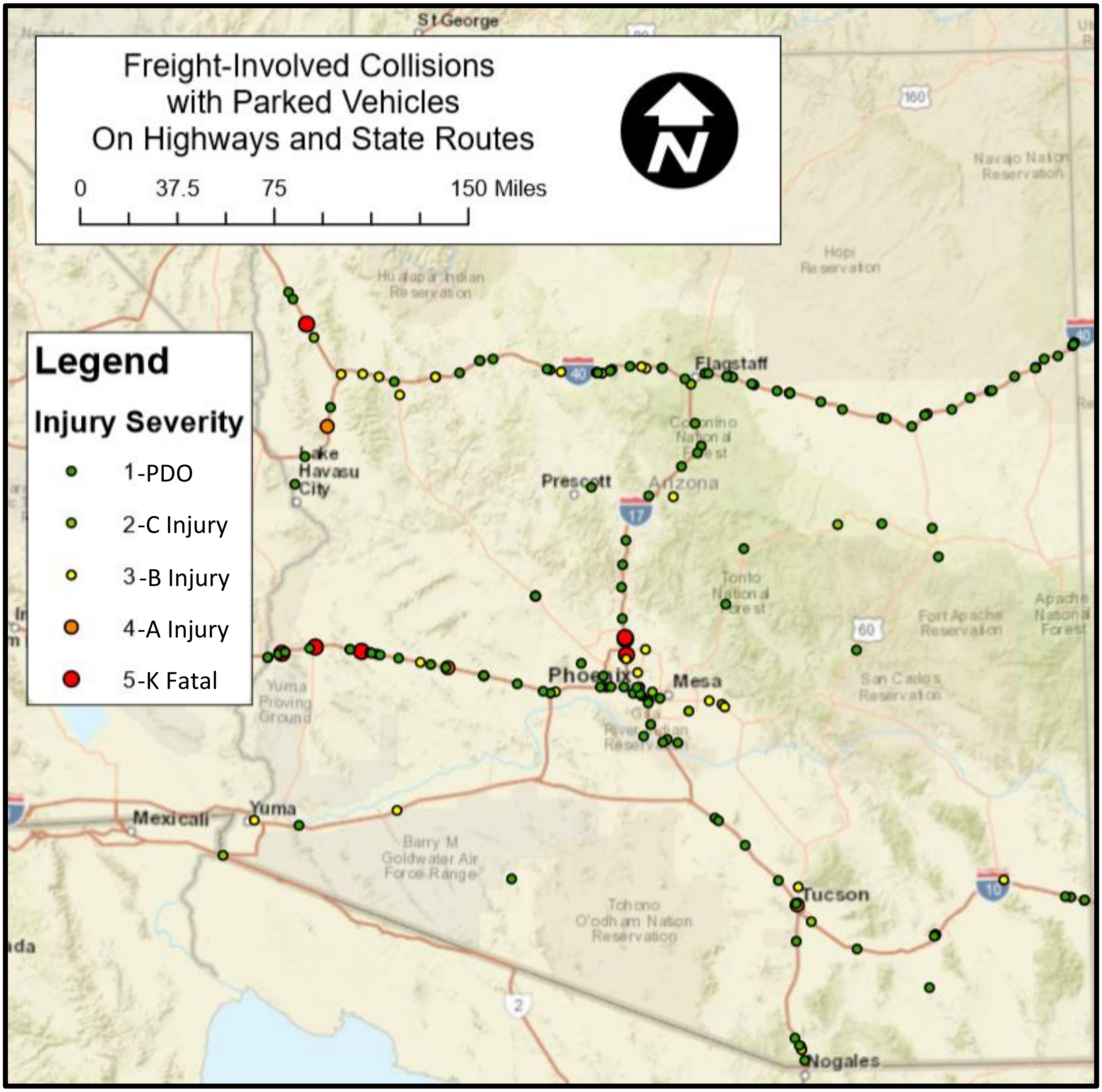

Figure 4.1: Freight-involved collisions with parked vehicles on highways and state routes

4.3 Results

When considering the results of this analysis, it is important to know that more than 50% of the I-10 is within a 10 mile radius of a public or commercial truck stop as shown below in Figure 4.2.

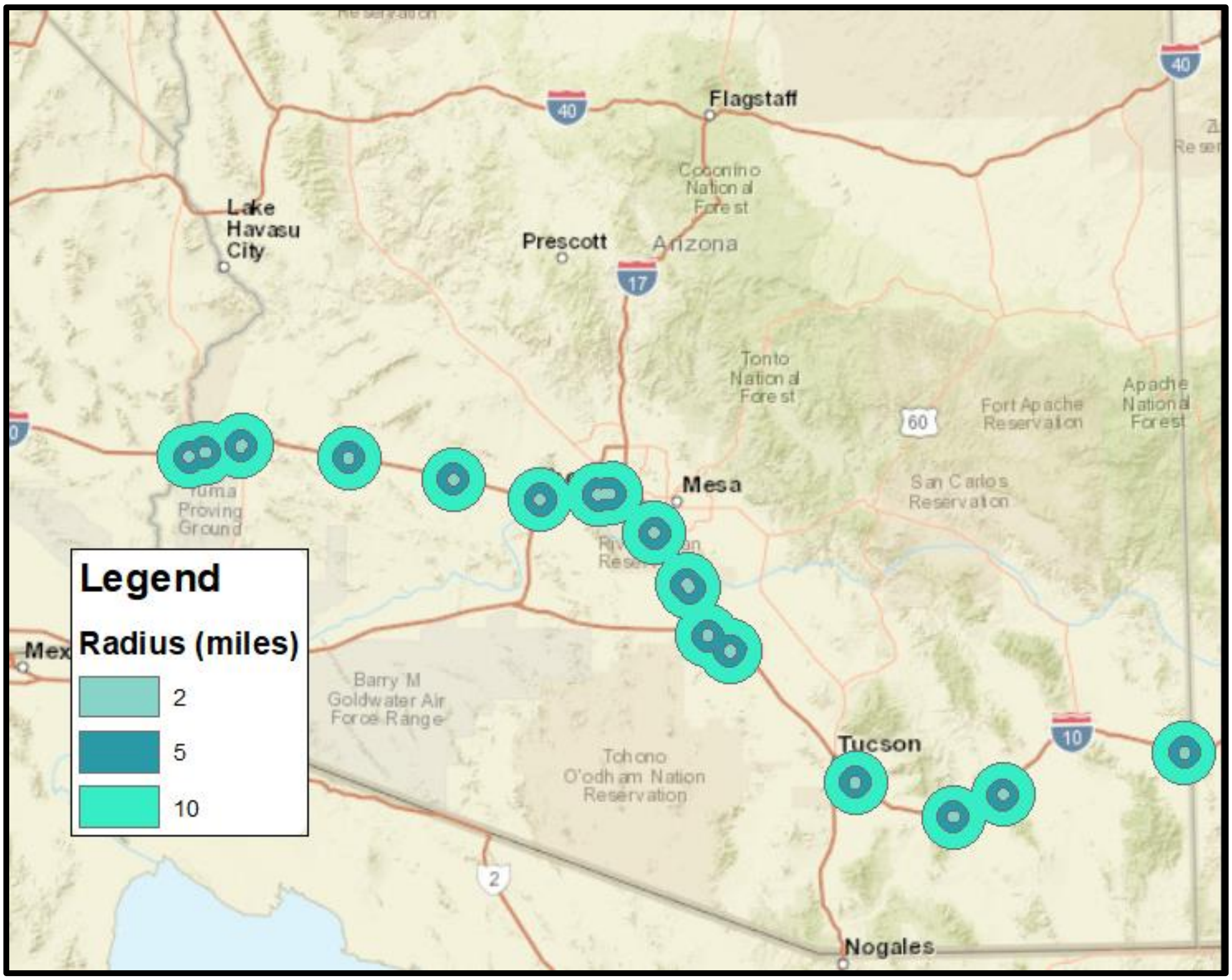

Figure 4.2: Buffer zones for public and commercial rest stops on the I-10

Figure 4.2 includes all public rest stops as well as Loves and Pilot commercial rest stops. This is evidence that there are many existing truck stops but there are still concerns over the limited spacing. Instead of building new truck stops, existing truck stops should consider implementing intelligent truck parking systems to help truck drivers plan their stops in advance and limit illegal truck parking.

The initial goal of this parked vehicle analysis was to conduct a severity analysis to determine the significant factors affecting crashes with parked freight vehicles. Similar to the severity analysis in section 3, the 185 crashes were broken down into occupants for a total of 479 occupants. Summary statistics of these 479 occupants can be seen below in Table 4.1

Table 4.1: Percent of total occupants by explanatory variable for parked vehicle occupants

Explanatory Variables		Percent of Total Occupants
Environmental	Inclement Weather	15%
	Other Weather	85%
	Summer	26%
	Fall	24%
	Winter	23%
	Spring	29%
Safety Device	No Safety Device	10%
	Safety Device	90%
Road Type	Freeway	69%
	Ramp	23%
	Other	10%
Injury Severity	O - PDO	80%
	C - Injury	3%
	B - Injury	8%
	A - Injury	2%
	K - Fatal	2%
Road Alignment	Uphill/Downhill	28%
	Level	72%
Work Zone	Workzone	6%
Collision Manner	Rear End	35%
	Sideswipe Same Dir.	48%
	Other CM	17%

When looking at this table, note that the injury percentages for these crashes are actually slightly higher than the total crash injury percentages in tables 3.1 and 3.2. From this observation, it is apparent that these particular crashes are in fact a concern in terms of injury severities.

These 479 occupants records were then used in an ordered logit model similar to the models discussed in section 3.2. Unfortunately, the model in NLOGIT did not converge because there was insignificant variation in the dependent variable. Therefore, similar to other studies of this nature, it was concluded that a statistical analysis cannot be used for this set of data to predict injury severity outcomes.

Despite the lack of observations and statistical significance, this study still considers the summary statistics and can make assumptions based on injury distributions and frequency associated with certain variables. Additionally, this study compares these summary statistics to the freight-involved summary statistics in Table 3.1. The summary statistics with relevant explanatory variables are presented in a similar fashion below in Table 4.2.

Table 4.2: Summary statistics for crashes with parked freight vehicles

Crashes with Parked Freight Vehicles							
	O-PDO	**C-Injury**	**B-Injury**	**A-Injury**	**K-Fatal**	**Total**	**% of Total**
All Crashes	135 (73%)	11 (6%)	29 (16%)	3 (2%)	7 (4%)	185	100%
Summer	35 (74%)	3 (6%)	5 (11%)	1 (2%)	3 (6%)	47	25%
Fall	29 (60%)	5 (10%)	11 (23%)	2 (4%)	1 (2%)	48	26%
Winter	35 (85%)	1 (2%)	4 (10%)	0 (0%)	1 (2%)	41	22%
Spring	36 (73%)	2 (4%)	9 (18%)	0 (0%)	2 (4%)	49	26%
Inclement weather	19 (70%)	1 (4%)	7 (26%)	0 (0%)	0 (0%)	27	15%
Non-Inclement weather	116 (73%)	10 (6%)	22 (14%)	3 (2%)	7 (4%)	158	85%
Dark Non-Lighted	40 (82%)	2 (4%)	5 (10%)	1 (2%)	1 (2%)	49	26%
Lighted Road Conditions	95 (70%)	9 (7%)	24 (18%)	2 (1%)	6 (4%)	136	74%
Rear End Crash	30 (48%)	7 (11%)	18 (29%)	2 (3%)	5 (8%)	62	34%
Sideswipe Same Direction	77 (87%)	3 (3%)	7 (8%)	0 (0%)	2 (2%)	89	48%
Other Collision Manner	28 (82%)	1 (3%)	4 (12%)	1 (3%)	0 (0%)	34	18%
Uphill or Downhill	38 (72%)	2 (4%)	12 (23%)	1 (2%)	0 (0%)	53	29%
Level Road Alignment	97 (73%)	9 (7%)	17 (13%)	2 (2%)	7 (5%)	132	71%
Ramp	30 (73%)	2 (5%)	8 (20%)	0 (0%)	1 (2%)	41	22%
Freeway	91 (72%)	8 (6%)	19 (15%)	3 (2%)	6 (5%)	127	69%
Other Road Type	14 (82%)	1 (6%)	2 (12%)	0 (0%)	0 (0%)	17	9%

When looking at overall injury distributions, the injury crashes were still over represented when only considering the most severe occupant injury in each crash. The frequency of crashes were split among seasons similar to all freight-involved crashes on the I-10. According to the FHWA Road Weather Management Program *(40)*, 22% of crashes are weather-related however, only 15% of crashes with parked freight-vehicles in Arizona are weather related. Contrary to expectations, dark non-lighted conditions did not appear to have a large impact on injury severity or frequencies.

As expected, 77% of all crashes with parked vehicles had a collision manner of either rear end or sideswipe same direction. Also as one might expect, rear end crashes had much higher injury severities than sideswipe same direction crashes. This again indicates the strong need for keeping vehicles from drifting out of their lanes while traveling on highways.

One explanatory variable that was not used in any of the previous analyses but is of interest here is whether or not the crash occurred on a ramp or on the freeway itself. In many cases, trucks will park on interchange ramps near truck stops when spaces fill up. As expected, there was a relatively high frequency of crashes with parked freight vehicles on ramps at 22%. However, injury severity did not appear to be significantly different for ramp crashes vs. non-ramp crashes. This could be due to lower speed differentials on ramps.

Overall, crashes with parked freight vehicles do happen at a rate of about 31 crashes per year in the state of Arizona. Additionally, these crashes have slightly higher injury severities than all freight-involved crashes on the I-10 and a large percentage of them occur on freeway ramps. This analysis also supports the necessity reducing lane departure crashes as full rear end crashes had much higher injury severities than sideswipe same direction crashes.

5.0 Potential Counter Measures

The results of this study along with industry trends suggest that emerging Intelligent Transportation Systems (ITS) technology should be considered as a solution before making traditional geometric or infrastructure improvements. Various different ITS technologies have been developing into mainstream applications through the use of advanced wireless communications and computer systems. Ideally, ITS will maximize the safety and efficiency potential for any existing street, intersection, or freeway. For the purpose of improving the safety and efficiency of freight movement on the I-10, this project proposes implementation of truck platooning, advanced driver assistance systems, real time truck parking information, or active traffic management. One of the main downsides to ITS right now is that for many of these systems, it is difficult to accurately quantify the possible benefits. This section will introduce each ITS technology and summarize some of the expected benefits based on past studies.

5.1 Truck Platooning

Truck platooning is an emerging technology that relies on Cooperative Adaptive Cruise Control (CACC) to help trucks drive safer, reduce fuel consumption and increase highway capacity. The USDOT estimates that truck platooning can "potentially result in significant benefits for goods movement to and from the major ports, as well as long-haul cross- country routes" *(41)*. CACC uses a combination of forward-looking radar sensors and electronic actuation of engine and brakes along with vehicle-to-vehicle (V2V) communication to automatically control the gap between a lead vehicle and a following vehicle or a series of following vehicles. Figure 5.1 provides a conceptual rendering of this interaction and Figure 5.2 illustrates the communication process from truck to truck.

Figure 5.1: Conceptual wireless communications for truck platooning *(41)*

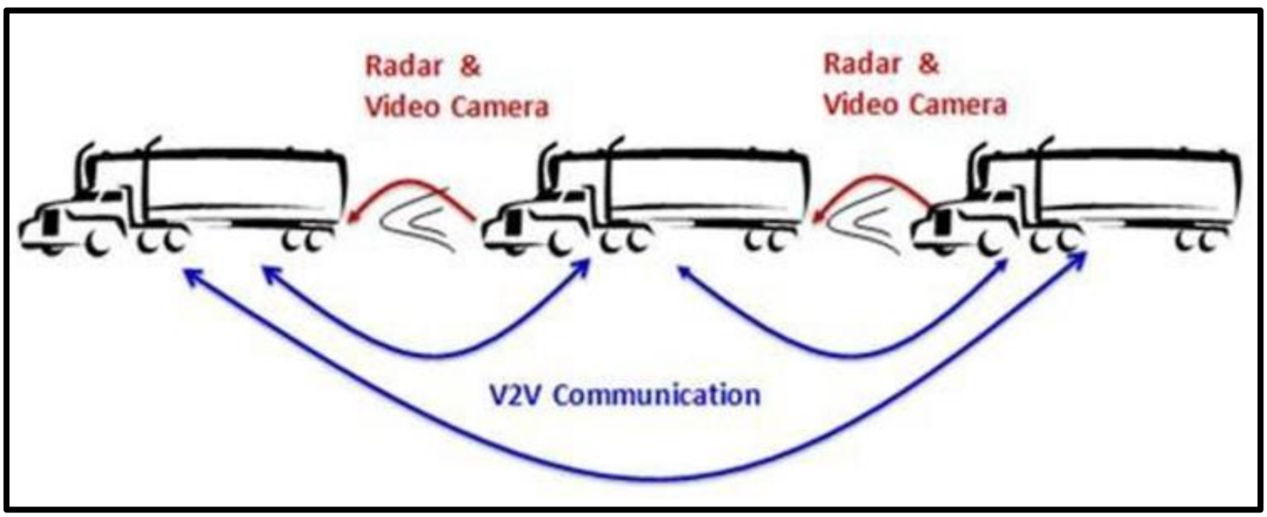

Figure 5.2: Truck platooning V2V communication diagram *(41)*

A study completed in Sweden in 2014 estimates that heavy vehicle platooning would result in fuel savings between 1 and 10% depending on the number of vehicles equipped with the technology as shown in Figure 5.3. Another study completed in the Netherlands in 2015 assumes an average 10% reduction in fuel consumption for two truck platoons and it also assumes 8% savings in resting times per day. This study concludes by estimating that truck platooning may be applicable by 2020 *(43)*.

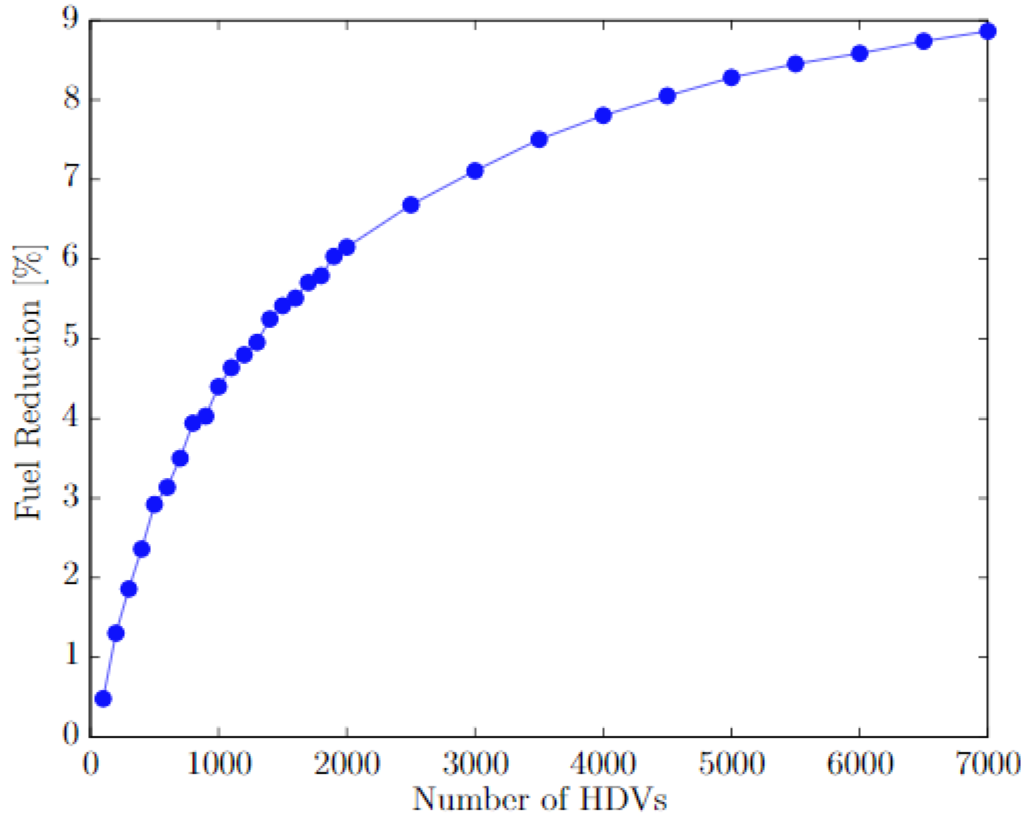

Figure 5.3: Expected fuel savings by size of heavy duty vehicle fleet *(42)*

No studies have been found that have been able to accurately quantify expected safety benefits associated with truck platooning, however, the scientific community appears to agree that there will be fuel savings of around 10% associated with truck platooning technology. Additionally, it is possible that certain truck on truck rear-end collisions may be prevented by using this technology. Overall, benefits for truck platooning are somewhat unrefined due to a lack of empirical data, however, there is agreement that it will bring economic benefits to the industry.

5.2 Advanced Driver Assistance Systems

Certain Advanced Driver Assistance Systems (ADAS) have nearly become a standard in the auto industry. Many auto manufacturers are already producing vehicles with collision warning, lane departure alerts, and adaptive cruise control systems installed. Figure 5.4 is a diagram created by Intel that lists many of the available in-vehicle driver assistance technologies on the market today *(43)*. Figure 5.5 is another diagram created by Intel that is an example of the many different ADAS sensors used to run each of these systems *(44).*

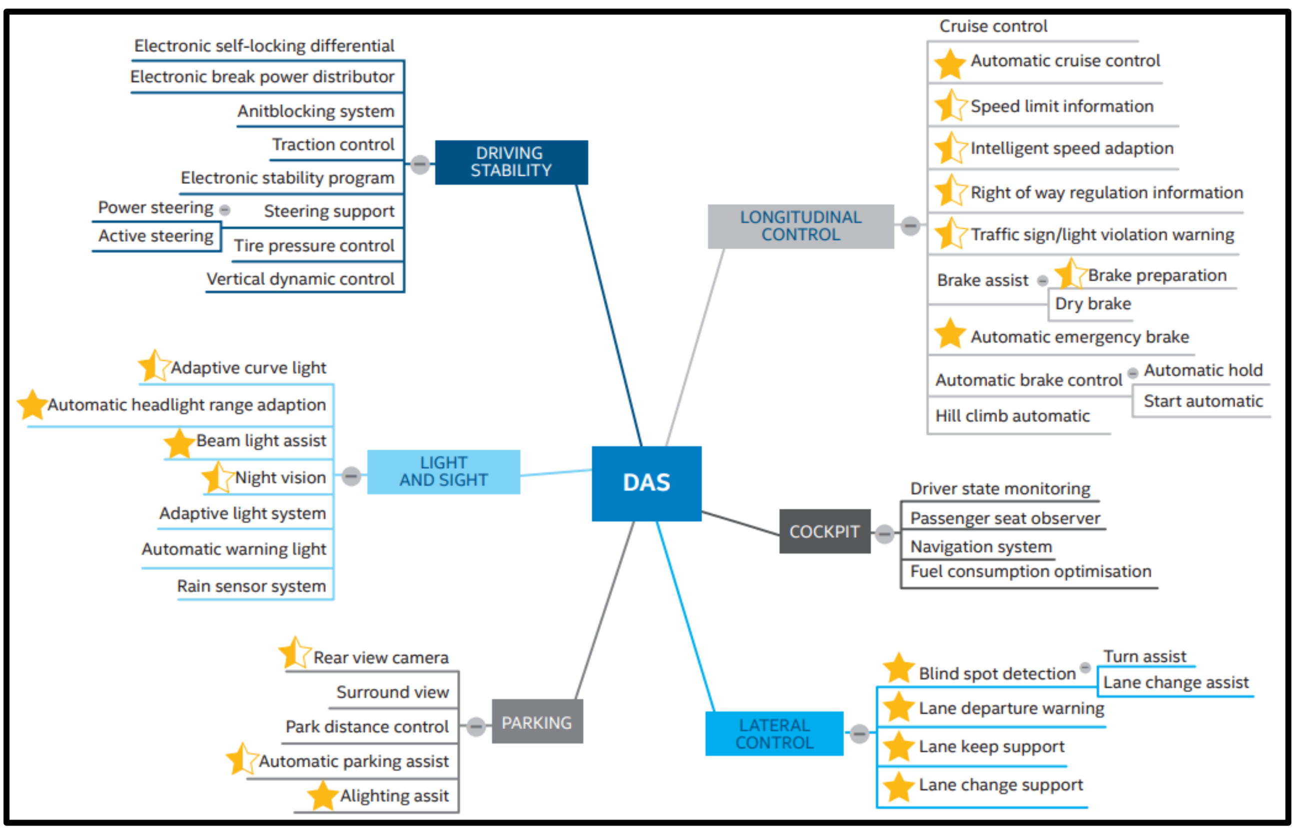

Figure 5.4: Spectrum of ADAS functions *(44)*

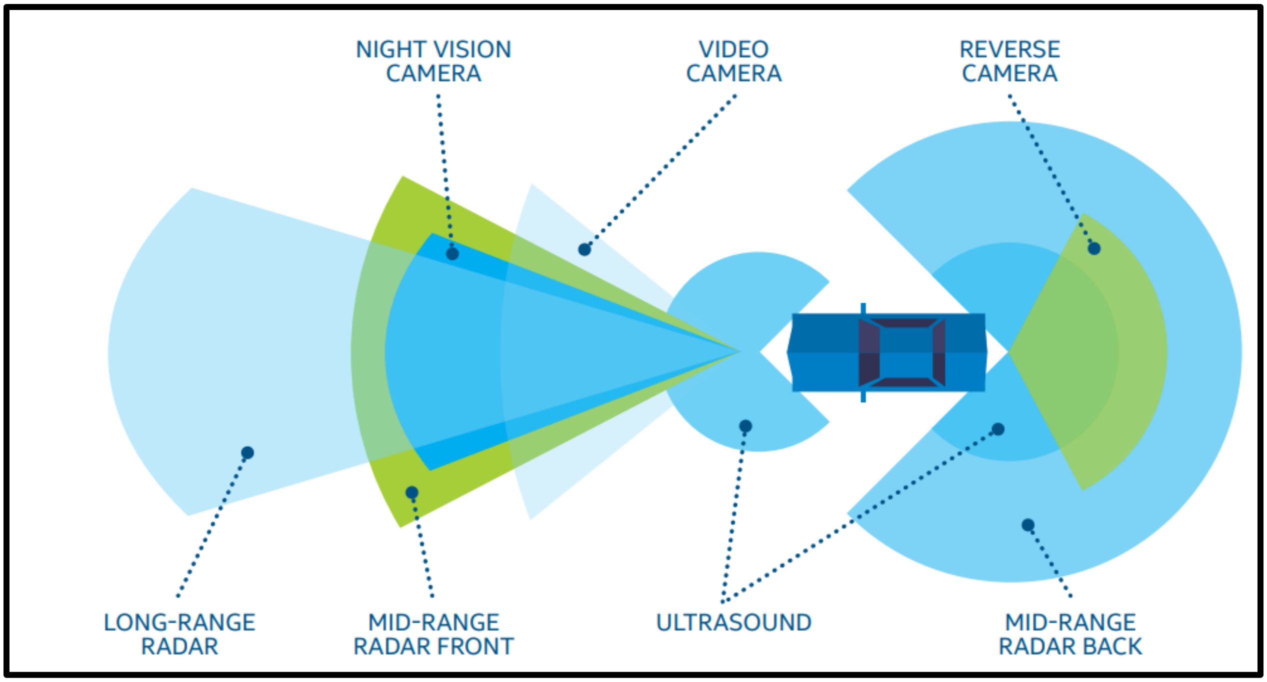

Figure 5.5: Example of ADAS Sensors *(44)*

In 2014, a study was completed at Monash University in Australia that estimates potential safety benefits of emerging crash avoidance technologies in Australian heavy vehicles *(45)*. This study concluded that more than half of all heavy vehicle injury crashes could be potentially prevented and nearly 70% of heavy vehicle fatal crashes could be prevented by using autonomous emergency braking systems *(45)*.

With many trucks already being equipped with this technology, there should soon be empirical data to support the expected safety benefits. There are, however, some challenges associated with these technology. The decision is currently being left up to the consumer on if they want spend the extra money to have this technology in their vehicle. If the government began to mandate and/or subsidize the installation of these technologies in all new vehicles then real safety improvement would be expected. Crash reports also may need to be updated to consider feedback from the vehicles computer system. For example, a data log could be incorporated into all ADAS on trucks that would continuously record computer and driver actions and could be used to better understand crashes. Another challenge associated with quantifying safety benefits is that many of the crashes that are prevented with technology will never be recorded or analyzed.

While there are many potential safety benefits associated with ADAS, many of these benefits are not easily quantifiable. Also, there are no mandates on installing this technology in new vehicles. Additionally, new concerns have arisen about the drivers over reliance on these assistance systems which may counter act the expected safety benefits. Ultimately, this is another technology that needs more research and time to fully understand its capabilities and influence on transportation.

5.3 Real-Time Truck Parking Information

Real-Time Truck Parking Information may be a cost effective, temporary solution to the truck parking issue from section 4. The idea is that both commercial and public truck stop destinations along the I-10 corridor would implement a truck parking information system that would utilize in-pavement or video detection devices to keep a continuous count of available truck parking spaces. This technology, along with strategically located variable message signs and a mobile app would help truck drivers plan their routes in advance and theoretically reduce the number of illegally parked trucks on the freeways shoulder or on ramps. Reducing these illegal parking instances would also result in less crashes would parked freight vehicles. Figure 5.6 is a picture of an existing HNTB variable message sign displaying available truck parking spots at upcoming exits in Michigan *(46)*. Figure 5.7 is a picture of the video detection device that the HNTB truck parking information and management system uses at participating truck stops *(46)*.

Figure 5.6: Variable message sign with truck parking availability *(46)*

Figure 5.7: HNTB 360 degree video detection device *(46)*

This is another means of maximizing the efficiency of existing infrastructure without physically building new facilities. There are some perceived challenges associated with this technology as well. For example, the initial safety benefits may be small and hard to quantify since the total number of crashes that this technology could prevent is already relatively small so many years of after data would be needed to properly quantify the safety benefits. Another challenge would be getting the funds to implement a project of this nature. Commercial trucks may be initially opposed to spending their own money to create this system without a guaranteed economic benefit. Trucking companies, state DOTs, and road users would benefit the most from this technology.

In May 2016, the University of Michigan transportation research institute completed a study that estimated the benefits of the HNTB and MDOT project recently mentioned. The study analyzed before and after crash data and surveyed 60 truck drivers *(47).* The survey concluded that drivers overwhelmingly agreed that parking information systems were personally valuable to the driver and could save them time in driving. Drivers appeared to overwhelmingly find the road sign sources both clear and useful, suggesting that acceptance of this source to be quite high. The crash analysis was inconclusive because of the limited area of implementation of the pilot parking information system *(47).*

Another study completed in Oregon in 2018 has identified freeway and ramp parking by truck drivers as an emerging safety concern on Oregon highways. The study used survey results to suggest that age and years of driving experience are key factors in the truck driver's decision to park illegally. It also stated that a possible solution would be to implement real-time information for truck parking and assess its impact on the number of trucks parked on freeway ramps and shoulders *(48)*

5.4 Active Traffic Management

Active Traffic Management (ATM) is another relatively new technology that could be implemented in the urban areas of Phoenix and Tucson to improve freight mobility. The idea behind ATM is that it allows agencies to have nearly full control over freeways in order to optimize capacity and efficiency while also improving safety. Currently only a few states in the U.S. have invested in an ATM system. However, ATM is becoming relatively common in Europe. The FHWA listed some of ATMs benefits that were observed on European freeways *(49)*:

- An increase in overall capacity of 3 to 22 percent
- A decrease in primary incidents of 3 to 30 percent
- A decrease in secondary incidents of 40 to 50 percent
- An overall harmonization of speeds during congested periods

In 2013 an initial crash benefit study was completed for an ATM segment on the I-5 in Seattle. In this study they observed a total crash reduction of 12 percent during the 2.5 years after installation *(50)*. A news article also reported on the effects of ATM on the I-5 by confirming crash reductions but also stating that travel times were not affected *(51)*.

ATM is often designed by installing sensors along the corridor to calculate real time speed, and volume at strategic locations. This information is then fed into an algorithm and used to alter the flow of traffic entering a congested area through the use of dynamic or variable message signs. The variable message signs are typically installed every half mile. Figure 3 illustrates typical dynamic message signs that would be used on an ATM corridor *(52)*.

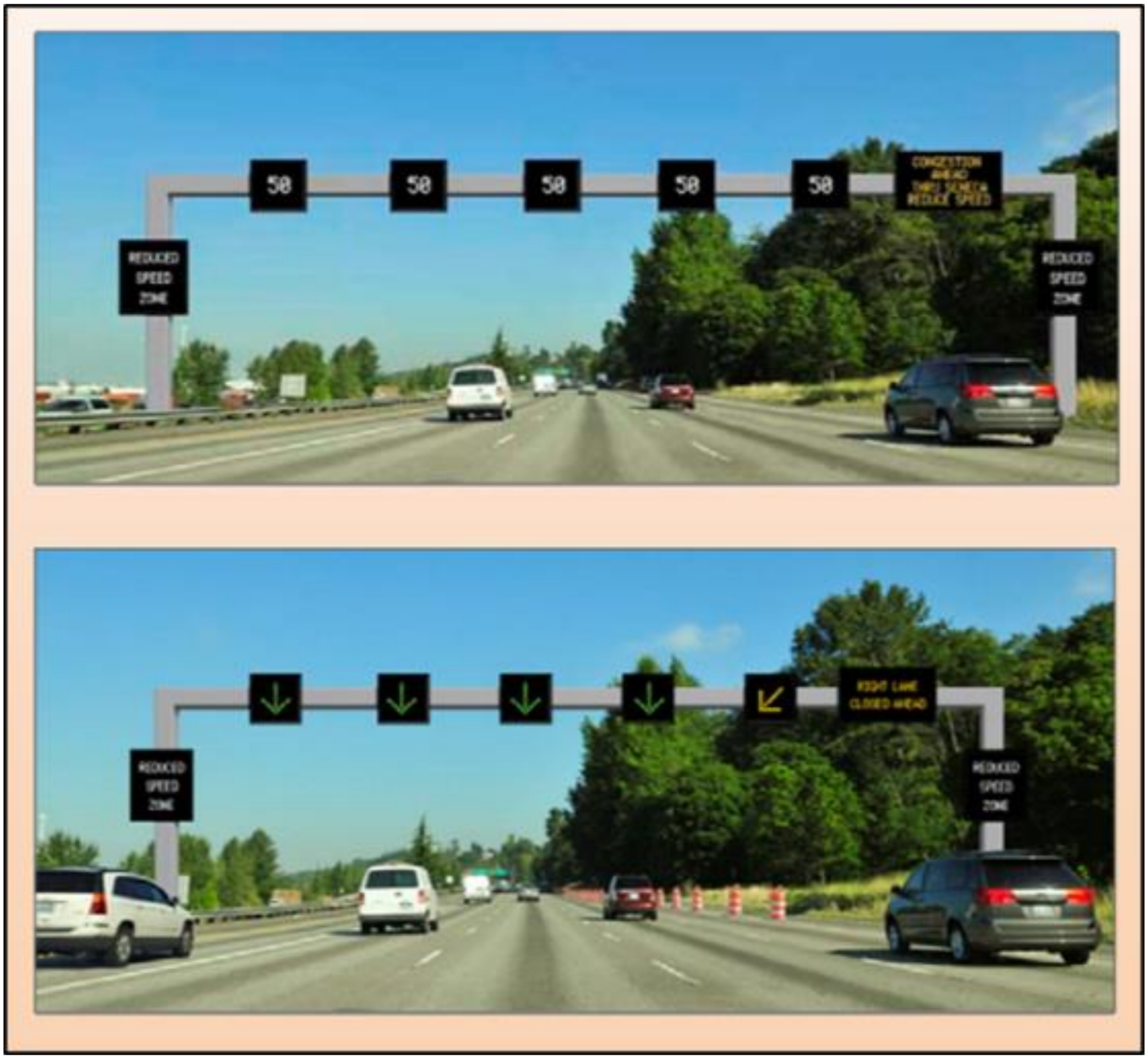

Figure 5.8: HNTB 360 degree video detection device (51)

Most of the past ATM studies have shown a large variation in effectiveness. These varying results are likely due to the many different types of ATM systems. Again, because this a relatively new technology, there is no “cookie cutter” way of designing an ATM system and all such projects are unique in more ways than one. For the I-10, an ATM system in Phoenix would require a large upfront investment to install all of the necessary equipment. However, if designed properly, it could result in large benefits to the state and freight movement through the state.

6.0 Conclusions

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 US 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. >80ft.) and low (i.e. <39ft.) 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 in the severity of freight-involved crashes but it was 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. Truck platooning may help reduce the frequency and severity of rear end crashes. Active traffic management 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.

While it was not possible to create a conclusive statistical model to understand what factors affect crashes with parked freight vehicles. Summary statistics of these crashes across the state show that they are in fact a safety concern with high injury percentages and unique characteristics. Crashes with parked vehicle may be mitigated by implementing a real-time truck parking system that will help truck drivers plan their routes and avoid illegally parking on freeway shoulders or ramps.

6.1 Limitations and Discussions for Future Research

There were two main limitations with this study. The first was a lack of accurate geometric data on the I-10. Many of the geometric characteristics assigned to the study segments were average or weighted values due to discrepancies between the segment lengths and start points of the AADT segments and the geometric variable segments. The second limitation was the lack of data for collisions with parked freight vehicles. A specific more defined variable in the crash reports would help to better understand these 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. More data is required to fully understand the emerging safety concern associated with limited truck parking, and illegal parking on or near freeways.

Another study that would help to better understand the findings from this study should be focused on understanding how if and how geometric highway characteristics affect freight-involved crashes. Several of the results in this study suggested that freight-involved crashes may be less affected by geometric highway design than non-freight crashes. However, more research is needed to make any significant conclusions.

More research also needs to be done on the safety impacts of the four ITS technologies presented in the potential countermeasures section. These studies will undoubtedly happen in time as these technologies become more common. However, at this time, the lack of empirical data for all these countermeasures makes it difficult to get accurate safety benefit predictions.

One last study that could complement this research would be a similar research project that considered even a broader area with more interstates and similar characteristics. Such a study would provide larger sample sizes and therefore could help to solidify some of the results and identify more significant factors in the frequency and severity of freight-involved and non-freight crashes.

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