Effects of Asphalt and Concrete Pavement Rehabilitation on Users and Businesses during Construction

by

Mitchell P. Fisher II

A thesis submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Master of Science

Auburn, Alabama
August 4, 2018

Keywords: Business Impacts, Crash Mitigation, Crash Severity,
Road User Costs, Transportation, Work Zone

Approved by

Jeffrey J. LaMondia, PhD, Associate Professor
Rod Turochy, PhD, Professor
Wesley Zech, PhD, Professor

ABSTRACT

Roadway maintenance and rehabilitation are critical tasks to sustain our transportation system. However, these activities often generate delays to road users, which can result in road user costs, work zone crash costs, and local business impact costs. This thesis presents a comprehensive methodology to calculate these costs and a tool developed for engineers and project managers to implement this methodology in practice. Specifically, this work develops methods for calculating a) road user costs, which adapts and updates FHWA and AASHTO policies, b) work zone crash mitigation costs, using an ordered probit model of crash severity estimated from eight states' work zone crash databases, and c) local business impact costs, using another ordered probit model of driver behavior change estimated from a nationally-representative survey conducted for this work. To our knowledge, this is the first example of local business impact costs being studied on a nationally transferable scale. Results showed roadway geometry played a heavy role in work zone crash severity with the posted speed limit being the most statistically significant. For local business impacts, travelers' decisions were most influenced by expected delay time, showing delay times exceeding 20 minutes resulted in travelers choosing to go somewhere else. Finally, an Excel-based tool was developed that completes a simulation of travelers through the work zone and calculates the costs for the project.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway Transportation Officials
AC	Asphalt Concrete
ADT	Average Daily Traffic
ALDOT	Alabama Department of Transportation
AMDT	Average Monthly Daily Traffic
BLS	Bureau of Labor Statistics
CMC	Crash Mitigation Cost
CO	Carbon Monoxide
CPI	Consumer Price Index
CTPP	Census Transportation Planning Products
CU	Combination Unit Freight
DOT	Department of Transportation
EC	Emission Cost
EMFAC	California Emission Factors Model

EPA……………………………...……….………………Environmental Protection Agency

FHWA………………………………....…..…………Federal Highway Administration

GDOT…………………………...………………Georgia Department of Transportation

HERS-ST…….…………..………………Highway Requirements System - State Version

HSIS………………….……………………………Highway Safety Information System

HSM………………….………………………...………………Highway Safety Manual

IRB……………………………………….………………Institutional Research Board

KABCO………………..…………………..………………FHWA's Crash Severity Scale

LBIC………………………………………………………..Local Business Impact Cost

LTC…………..……………………………………………………………Lost Time Cost

NOx……………………………………...……….………………………Nitrogen Oxides

OC………………………..…………………………………………………Operating Cost

PCC………………………………………….………………Portland Cement Concrete

PDO………………...…………………………..………………Property Damage Only

PENNDOT…………………….………………Pennsylvania Department of Transportation

PM2.5…………………….…………………………..………………Particulate Matter

PRPC……………………………………………Pavement Rehabilitation Project Cost Tool

RUC…………………………………………..……………………………Road User Cost

SU……………………..…………………………………………….Single Unit Freight

TTI……………………………………….....…….Texas A&M Transportation Institute

VMT…………...……………………………..……………….Vehicle Miles Traveled

VOC……………………..………………….……………….Volatile Organic Compounds

VoT………………………………………………………………………Value of Time

VoR……………………………………………………………...…..Value of Reliability

CHAPTER 1: INTRODUCTION

Roadway maintenance and rehabilitation are critical and ubiquitous activities for state, county, and city engineers across the country. With this task, engineers constantly identify effective and efficient scheduling and rehabilitation methods that offer the lowest impact on local users and businesses. These blanketing costs need to be considered in the pavement type selection process and construction scheduling which this thesis will attempt to cover.

Past research regarding lifecycle cost analyses tends to focus a limited scope on construction-related costs (Asphalt Pavement Alliance, 2011, 2016), while other sources and studies are currently out-of-date or simplified (ASCE, 2014; Babashami, Yusoff, Ceylan, Nor, & Jenatabadi, 2016; Borchardt, Pesti, Sun, & Ding, 2009; Mallela & Sadavisam, 2011). There are many factors affecting Road User Costs (RUCs), crash mitigation costs, and local business impact costs that need to be simultaneously accounted for to accurately calculate cost values. Most importantly, no relevant data-driven work exists to quantify local business impacts of work zones beyond broad discussions about including local business owners in project planning (Borchardt et al, 2009; Daniels, Ellis, & Stockton, 1999; Mallela & Sadavisam, 2011).

Therefore, the objective of this thesis is to update the white paper *Estimating User Costs of Asphalt and Concrete Pavement Rehabilitation* (Memmot & McFarland, 1988) by:

- Developing a comprehensive set of data-driven, nationally transferrable metrics that quantify the costs associated with asphalt and concrete pavement rehabilitation in terms of (a) road user costs, (b) crash mitigation costs, and (c) local business impact costs.
- Presenting how these costs vary by (a) types of pavement rehabilitation, (b) surrounding development (urban vs rural), and (c) types of scheduling alternatives.
- Creating a convenient Excel tool for users to input project variables and receive associated direct and indirect costs.

This tool is intended for any engineer or project manager who needs a streamlined, general analysis of likely impact costs when planning for road rehabilitation scenarios requiring lane closures. Users can test different scheduling alternatives to determine the least impactful course of action. Engineers and project managers can implement the models and tool developed in the project to a) characterize the road user, crash mitigation, and local business impacts of an existing project or projects that are being let for bid; b) to evaluate possible innovative scheduling opportunities in the project planning stage; and c) to illustrate to local business owners the potential loss in revenue they could receive during construction.

This thesis is organized into chapters addressing each associated cost and the impact with the Excel tool. Chapter 2 presents a literature review of current methodologies and past research expenditures were collected and addressed. In Chapter 3, updated road user costs were compiled from several reputable sources and studies with a general example presented to guide the reader through the process. In Chapter 4 crash mitigation cost results were covered from research conducted across an eight-state data set regarding work zone crashes. Chapter 5 covers the methodology and results of the local business impact costs survey and model is addressed. A detailed, step-by-step user guide of the Excel tool is then presented in Chapter 6 with a subsequent real-world example is then given. Finally, conclusions and suggestions for future work from the project are shared in the final two chapters.

CHAPTER 2: LITERATURE REVIEW

Research regarding Road User Costs (RUCs) is a hot topic with years of research dedicated to the subject and multiple federally funded projects commissioned to validate claims. The two main sources for standard RUC values and methodology come from the American Association of State Highway Transportation Officials (AASHTO) and the Federal Highway Administration (FHWA) guides *User and Non-User Benefit Analysis for Highways* and *Work Zone Road User Costs: Conceptions and Applications*, respectively (AASHTO, 2010; Mallela & Sadavisam, 2011). In terms of work zone analysis, the FHWA methodology solely focuses on this topic offering a comprehensive guide for determining RUCs, as well as alternatives to some calculations—such as emissions—based on individual state specific research. However, most of the provided values are out-of-date by several years, or in some cases decades, which in turn can greatly underestimates the actual RUCs. AASHTO's methodology, while just as comprehensive, focuses mainly on RUC improvements from before and after a project is implemented which does in turn require some interpretation to convert to work zone related costs. As with the FHWA's methodology, the provided values are out-of-date by similar timeframes, but alternative sources are not provided to update easily. Additionally, this methodology assumes the user has several inputs on hand, such as average delay times and average hourly traffic; values that traditionally need to be gathered in the field for the best accuracy. Since RUCs are most useful when calculated before a project's implementation, these values need to be calculated off available information using methodology not directly sourced in AASHTO's approach. Nonetheless, some work has already been done to create ease-of-use spreadsheet tools to realistically predict an optimized work zone plan based on AASHTO and FHWA methodologies. Tang's work created a plug-and-play Excel spreadsheet tool centered on optimizing work zone scheduling to reduce RUCs, contractor operation costs, and idle time (Tang & Chien, 2009). As results are mainly a function of vehicular volume, a detailed chart of the expected hourly vehicle volume was required to properly utilize the tool. Although historical average hourly traffic (AHT) data could be used, the concept of "natural diversion", as Ullman pointed out, would not be accounted for (Ullman, 1992, 1996). This phenomenon is covered later in this chapter.

Texas A&M Transportation Institute (TTI) research on RUCs mostly falls into the same outdated pitfalls as the aforementioned FHWA and AASHTO methodologies with the added limitation of only being Texas-specific (Borchardt et al, 2009; Daniels et al, 1999). Granted, Borchardt's report was published in 2009 as opposed to Daniel's' in 1999, however Borchardt's tended to direct readers to outside sources and focused mainly on comparing industry software methodologies. Both reports used data pulled from the MicroBENCOST software, whose biggest drawback being the lack of vehicle emissions costs. For other reviewed publications, the focus tended to ignore costs outside of construction and the resulting operational life cycle costs (ASCE, 2014; Babashami et al, 2016).

2.1 CRASH FACTORS

When focusing on crash mitigation costs, FHWA's RUC publications provided a comprehensive analysis on crash rate calculations and their costs. However, the FHWA concludes by suggesting agencies assign their own crash modification factors since results vary from region to region as well as between published studies (Mallela & Sadavisam, 2011). AASHTO's methodology also provides a section on crash mitigation, but focuses mainly on crash frequency and individual costs as opposed to crash contributing factors (AASHTO, 2010). After further evaluation, several methods for determining work zone crash factors were identified from publications. Both Duncan's and Kockelman's successes with the ordered probit model in identifying crash injury thresholds proved to be promising in determining a viable predictive model (Duncan, Khattak, & Council, 1998; Kockelman & Kweon, 2002). Their methodology, which ultimately was chosen for this study, not only allowed the identification of statistically significant crash severity characteristics, but the ability to predict, given several road and driver characteristics, the probable crash severity to occur. Similarly, Li in his study used a simplified logistic regression model to determine the statistically significant crash severity characteristics of Kansas crashes (Li & Bai, 2008). The shortfall of Li's method is the lack of a resulting threshold calculation, so the user is left with identified significantly influencing crash factors but no way to probabilistically predict a possible crash scenario.

Bai also analyzed Kansas work zone crashes (n = 157) using a logistic regression model, but focused solely on fatal crashes (Bai, 2006). Responsible driver characteristics showed 75 percent of fatal work zone crashes were caused by males. Drivers ages 35 to 44 and drivers above the age of 65 were responsible for 24 percent and 18 percent of fatal work zone crashes, respectively. Relevant to this project, he also reported findings involving time of day and road classification. Bai found 32 percent of fatal work zone crashes occurred during non-peak hours (10AM to 4PM). Additionally, 37 percent of fatal work zone crashes occurred between the hours of 8PM and 6AM; with 32 percent occurring in areas of no illumination. The most alarming result stemmed from two-lane highway work zones, accounting for 73 percent of all analyzed fatal work zone crashes; over double of all non-work zone fatal crashes over the same time-period (35 percent). In addition, he found inclement weather and day of the week did not significantly contribute to crashes fatalities.

Regarding actual work zone crash mitigation techniques, Meng found in a study of long-term work zones that a 20 percent reduction in the speed limit resulted in a 62 percent decrease in fatality risk (Meng, Weng, & Qu, 2010). In that same vein, it was found that reducing the work zone speed was more effective than reducing the emergency response time. When construction workers were surveyed in Debnath's Australian study, they identified wet weather, speeding, and nighttime conditions as perceived hazards to both worker and motorist safety (Debnath, Blackman, & Haworth, 2015). Khattak's analysis of California freeway work zone crash rates identified increased crash rates with increases in average daily traffic, work zone length, and work zone duration; with duration being the most significant factor (Khattak, Khattak, & Council, 2002). Overall, Khattak found a 21.5 percent increase in total crashes from pre and during work zone conditions. As this report's model is analyzed, it would be expected these factors would play heavily in crash severity determination to validate these hypotheses.

Overall, five main crash characteristic trends were identified:

- Weather conditions did not significantly contribute to crash severity (Bai, 2006; Debnath et al, 2015; Duncan et al, 1998). As well as day of the week (Bai, 2006).
- Head-on, angle, rollover, and rear-end crashes lead to the most crash fatalities (Bai, 2006; Li & Bai, 2008).
- As driver age increases, the chance of a high severity crash increases (Bai, 2006; Li & Bai, 2008). Additionally, drivers ages 35 to 44 were overrepresented (Bai, 2006).

- Dark, non-lit road conditions resulted in higher crash rates according to the literature (Bai, 2006; Debnath et al, 2015; Duncan et al, 1998; Kockelman & Kweon, 2002).
- Full and partially controlled road access resulted in less severe crashes and crash rates (Gluck, Levinson, & Stover, 1999; Schultz, Braley, Boschert, 2009). Two-lane roads were the most dangerous in terms of crash rates and severity (Bai, 2006), even though evidence has suggested otherwise (Harwood, Council, Hauer, Hughes, & Vogt, 2000).

2.2 LOCAL BUSINESS IMPACT COSTS

Regarding local business impact costs, very little prior research has been done in the past, and from what can be determined, not a single study has been conducted on a national scale. For the existing reports, FHWA's RUC methodology offers references to previous studies, discussed below, but takes a qualitative rather than quantitative approach to the subject; while AASHTO only discusses the possible long-term benefits of improvement projects to the local economy. The first report FHWA refers to is a series of TTI studies completed in the late 90s on road-widening projects. Wildenthal and Buffington surveyed affected business owners on their thoughts and experiences during construction and compared their answers to field data (Buffington & Wildenthal, 1997; Wildenthal & Buffington, 1996). Data from the abutting businesses' gross sales showed a 5 percent decrease during construction which was not nearly as negative as business owners originally perceived. However, these abutting businesses received higher traffic from construction workers so net loss from regular customers could not be fully calculated.

The other recommended report from FHWA referred to a multiyear study for the town of Dubois, Wyoming, during a major highway improvement project (Buddemeyer, Young, & Vander Giessen, 2008). This report ended up being more comprehensive than the aforementioned TTI reports documenting before and after conditions and different mitigation technique impacts. Overall, data was gathered from businesses, traveler surveys, traffic counts, and general economic sources. From Buddemeyer’s conclusions, traffic volumes did decrease during construction, but the majority of surveyed local businesses stated they had seen no change in gross sales, the number of customers, and net profit. Wyoming Department of Revenue data backed this claim showing the health of individual businesses was “very positive” once all individual businesses were equally weighted. Additionally, of the mitigation techniques employed to limit loss of business, an active public marketing campaign proved to be the most effective.

When the section of Interstate 5 running through Sacramento, California was subject to “The Fix” improvement project, Ye and his group conducted a study on commuter responses through a series of surveys and field data counts (Ye, Mokhtarian, & Circella, 2012). Their non-work activity results found 44 percent of those surveyed changed their regular routes to avoid delays and construction. Additionally, more than 20 percent changed either the location or time of their activity, with 18 percent changing the day of the activity, and an additional +20 percent choosing to cancel the activity all together.

2.3 NATURAL DIVERSION, VALUE OF TIME, AND STORE LOYALTY

Briefly mentioned earlier, the concept of “natural diversion” plays a heavy influence in work zone/incident vehicular flows. Ullman defines the phenomena as the voluntary avoidance of delay (i.e., work zone, incidents, special events, etc.) without prompting by traffic control planning or enforcement personnel (Ullman, 1992, 1996). As RUCs, crash rates, and business impacts are directly tied to traffic flows, this concept is of the utmost importance. Although easily observed on freeways—because of their controlled access design—the concept has been applied to most road networks. Karim summed this concept into an equation (presented later) for work regarding work zone capacity and queue estimation. His equation accounted for a reduction in traffic volume due to four situations: travelers choosing alternative routes, travelers changing their schedule to avoid the work zone, travelers canceling their trips because of the work zone, and travelers changing their transportation mode (Karim & Adeli, 2003). While straightforward in nature, the downfall of this equation is the unpredictability of the diversion factor. Karim suggests obtaining the factor from similar work zone studies or network analysis models, but admits it acts more of a function of variable changes in delay. If diversion estimates were universally low, this would not be a huge issue, but as shown in Khattak's survey work of San Francisco Bay Area commuters, up to 40 percent of commuters could divert if warned ahead of time by an Advanced Traveler Information System (Khattak, Kanafani, & Le Colletter, 1994). This was from a 1993 study—before the ubiquity of smart phones—so it's not hard to imagine that commuters would be even more likely to divert given they have access to real-time delay estimates (Agrawal, Song, Peeta, & Benedyk, 2018; Thorhauge, Haustein, & Cherchi, 2016; Yu & Peeta, 2011).

Factors that influence diversion have been found in several studies using stated preference surveys. Song's 2007 study of Florida commuters tested results of a statewide survey against a discrete choice model (testing for utility of an alternate path) (Song, Yin, & Srinivasan, 2011). Included in the test was travel time, trip purpose (to work, to home, leisure), location (rural or urban), socioeconomic factors, and weather/road conditions. Results found only travel time (t_{calc} = -10.16) and rural location (t_{calc} = 2.84) were statistically significant in influencing route choice. As travel time increased, travelers were more likely to choose an alternative route. However, as travel time of an alternative route increased, travelers were more likely to stick with their original route. To put it quantifiably, for every minute increase of travel time for either route, utility for that route decreased by 0.1416 (utility is a unit-less value). This suggested travelers equally weigh their original and alternative route choices. Rural locations resulted in travelers more likely adhering to their original routes; as rural road networks offer fewer alternatives. Sing also argued the inclusion of weather (t_{calc} = 1.58) being significant in route choice, even though it tested statistically insignificant (t_{crit} = 1.645). Interpreted, travelers were more likely to divert from their original route when facing poor weather conditions. This was in line with Khattak's earlier study (Khattak et al, 1994). Khattak's study also found that individuals were more likely to divert if they took a higher number of recreational trips per week, implying individuals who drove more, may be more willing to divert, or knew the road network better. Additionally, there is also the possibility of commuters permanently switching their routes due to prolong road network change; as demonstrated in the Minneapolis I35W bridge collapse (Di, Liu, Zhu, & Levison, 2017). Di's team found that even after the I35W bridge was rebuilt, traffic volumes never returned to their initial levels, thus demonstrating how prolong work zone delays can affect future traffic levels.

Another factor to consider for natural diversion is an individual's value of time (VoT). Value of time refers to an individual's perceived monetary value of a set amount of time experienced. If an individual has a lower VoT, they would be less likely to change their decision. Generally, VoT is used to determine how travelers would react to toll road implementation (Lam & Small, 2001) or mode choice (Outwater, Castleberry, Shiftan, Ben-Akiva, Shuang, & Kuppam, 2003; Van Nostrand, Sivaraman, & Pinjari, 2013), but it has been used for route choice showing uncongested conditions produced lower VoTs than congested conditions (Calfee & Winston, 1998; Small, 1999). Lam found under congested conditions, that men had a higher VoT ($19.22/hour) compared to value of reliability (VoR) ($11.90/hr) than females (VoT = $19.22/hour; VoR = $28.72/hr), but females had a higher VoR (Lam & Small, 2001). This would suggest females would be more likely to choose a route with little variability in travel time, while males would be more likely to choose the fastest overall route. The concept of travel time reliability (i.e., VoR) was further defined by Pinjari, who found trips under 15 minutes had a higher VoR than VoT (a VoR-to-VoT ratio of 201 percent), but trips over 15 minutes saw the relationship rapidly decrease (Pinjari & Bhat, 2006). Several studies had also found VoT increases as household income increases (Calfee & Winston, 1998; Lam & Small, 2001; Van Nostrand et al, 2013). Outwater's survey of San Francisco travelers found through factor analysis and regression models that people are more concerned with finding the fastest route than experience delays (Outwater et al, 2003). The same study found households with kids and larger households (greater than 3 individuals) had a greater need for time savings than households with no kids and smaller households, respectively. Age was more of a polarizing factor. Lam's study found that age was not statistically significant in VoT, but Van Nostrand and Outwater found the opposite. Additionally, psychological sources support the latter as Agahi and Atchley have proposed. Agahi found from a study of Swedish citizens that leisure participation had a stable rate of participation as age increased (Agahi, Ahacic, & Parker, 2006) suggesting older populations may continue to participate in their regular leisure activities regardless of negative impacts to their VoT. According to Atchley's continuity theory, people maintain patterns of activities, thought, and habits as a common strategy for adaptation to changes in daily life (i.e. retirement, bereavement, etc.) (Atchley 1989, 1993). This could further explain VoT findings showing older motorists having lower VoT and thus, less likely to change their plans.

So, what about the other individuals who still choose a route/destination even when another option is more easily available? In general transportation, there is the idea of "habitual/self-selection" when it comes to a person's bias in mode selection (Frank, Bradley, Kavage, Chapman, & Lawton, 2008; Gärling & Axhausen, 2003; Pinjari, Pendyala, Bhat, & Waddell, 2011). This theory states that individuals demonstrate a predisposition to choose one mode over another, even if an unchosen mode is more efficient—based on their past experiences and comfort level. This bias, along with the aforementioned personal value of time, can also be applied to how some individuals are less likely to go to a different store or choose another route (Bogers, Viti, & Hoogendoorn, 2005) when faced with an increase in delay. However, this review found previous studies focused solely on grocery stores—although this can still be applied to personal shopping to a degree. Cunningham presented this principle using panel data acquired from the Chicago Tribune (Cunningham, 1956, 1961). Using this data, he found that the average family makes 48.6 percent of its total food purchases at its favorite store, families are more loyal to chain stores than specialty/independent stores, and there was no correlation between socioeconomic factors and brand loyalty. Carman's study backed this claim, showing store loyalty reduced shopping around and in turn, saved time and money (Carman, 1969). This was also confirmed by Rao's study on the Chicago Tribune panel survey, but found store bias was the result of certain physical/service factors in the store and "economical and locational factors" of the family (Rao, 1969). Basically, families were less inclined to go to stores further away from their residence, unless an in-store service factor made the trip worth the effort. Rao also found bias in store selection was "strongly related to the most recent uninterrupted sequence of favorable choices of that store" (Rao, 1969), and paired with Cunningham's findings regarding total food purchases, would suggest families would be hard pressed to change their grocery store destination unless the journey exceeded their perceived value of time.

2.4 SUMMARY

Overall, this research heavily influenced the choice in using FHWA and AASHTO RUC methodology in the tool's design—mainly due to its simplicity and universal acceptance. As stated above, using an ordered probit model for crash mitigation costs was chosen to not only allow the identification of statistically significant crash severity characteristics, but to also allow the ability to predict, given several road and driver characteristics, the probable crash severity to occur. To the author's knowledge no similar research methods have been conducted previously to measure stated preference travel changes due to work zones. However, past work on stated preference surveys and results from analyses on driver diversion informed the survey development and hypotheses.

CHAPTER 3: ROAD USER COSTS

Road User Costs (RUCs) are the first of the three impact categories associated with roadway pavement rehabilitation work and quantified in this thesis. RUCs are defined as the total monetary and temporal costs experienced by both personal and freight vehicle road users when faced with delays caused by lane or total road closures due to rehabilitation work. While RUCs have previously been calculated under a variety of scenarios and for different population groups (Babashami et al, 2016; Borchardt et al, 2009; Daniels et al, 1999), this section provides a straightforward methodology for calculating RUCs for pavement rehabilitation work synthesized from these past best practices. Specifically, this chapter calculates a Total Dollar ($) per Day Road User Cost for any given work zone based on a) lost time costs, b) operating costs and c) emission costs. Additionally, this chapter provides information on how scheduling rehabilitation work can impact costs. All values provided have been adjusted to 2016 dollars using the Bureau of Labor Statistics' CPI calculator unless otherwise noted.

3.1 ROAD USER COSTS MODEL EXPLANATION

Road User Costs (RUC) for each vehicle *i* in a work zone are most often described using Equation 3.1:

$$RUC_i = LTC_i + OC_i + EC_i \qquad \text{(Eq. 3.1)}$$

Where:

RUC_i = Road User Costs for vehicle *i* (*dollars per vehicle*),

LTC_i = Lost Time Cost (*dollars per vehicle*),

OC_i = Operating Cost (*dollars per vehicle*), and

EC_i = Emissions Cost (*dollars per vehicle*)

Each component is calculated as dollars per vehicle and outlined in detail in the following sections. These RUCs can be calculated for each individual vehicle and summed for the entire volume of traffic that passes through the work zone. To streamline the process, instead of calculating for each vehicle, RUCs will be calculated for each vehicle class *c* instead. For the purpose of this thesis, three vehicle classes are specified: personal, single-unit freight, and combination freight, as defined by FHWA. It is important that RUCs for work zones be focused on impacts generated from the work zone beyond those experienced by motorists during normal traffic operations when the work zone is not present.

3.1.1 Impacts of Scheduling Rehabilitation Work on Costs

One of the simplest ways to minimize RUCs is to reduce the number of vehicles affected by the work zone. This can be achieved by scheduling projects during off-peak driving times. First, project managers can select a month or day of the week that minimizes the traffic volumes (as seen in Tables 3-1 and 3-2 (ITE, 1999)). These tables present the Average Daily Traffic (ADT) Factors for given months (Table 3-1) and days of the week (Table 3-2) for different roadway classifications in Georgia, as an example. To convert from Annual Average Daily Traffic (AADT) to Average Monthly Daily Traffic (AMDT) or Average Daily Traffic (ADT), respectively, simply divide the AADT by the appropriate factor. AADT can be found readily from most state or city DOT websites and other relevant sources. As for interpreting Tables 3-1 and 3-2 below, the higher the factor value, the smaller the estimated AMDT or ADT. Table 1 highlights that AMDT is greatest during the summer and fall months, so work zone projects completed in winter months will have lower overall RUCs when based solely on vehicle volume impacts. Similarly, Table 3-2 highlights that ADT is greatest during the weekdays with the greatest volumes occurring on Fridays and the lower volumes occurring on the weekend.

Table 3-1: GDOT AMDT Factors

Road Classification	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec
Rural/Small Urban Interstate	1.18	1.08	0.97	0.95	1.01	0.95	0.91	0.94	1.06	1.04	1.00	0.96
Rural Arterial	1.14	1.08	1.02	0.98	0.97	0.96	0.97	0.98	0.98	0.94	0.97	1.04
Rural Collector	1.20	1.05	1.00	0.95	0.95	0.98	0.97	0.95	0.98	0.94	1.03	1.05
Urbanized Interstate	1.11	1.05	0.99	0.99	0.99	0.94	0.97	0.95	1.01	1.00	1.01	1.03
Urbanized Arterial	1.06	1.01	0.99	1.01	0.96	0.99	1.02	1.00	0.99	0.96	1.00	1.03
Urbanized Collector	1.05	0.99	0.95	0.95	0.96	1.00	1.01	1.04	1.03	0.92	1.06	1.08

Table 3-2: GDOT ADT Factors

Road Classification	Sun	Mon	Tues	Wed	Thurs	Fri	Sat
Rural/Small Urban Interstate	0.99	1.07	1.12	1.08	1.02	0.85	0.93
Rural Arterial	1.29	0.99	0.99	0.98	0.95	0.85	1.04
Rural Collector	1.14	1.04	1.05	1.04	1.01	0.87	0.99
Urbanized Interstate	1.39	0.98	0.94	0.92	0.91	0.86	1.18
Urbanized Arterial	1.55	0.94	0.92	0.92	0.92	0.84	1.17
Urbanized Collector	1.57	0.95	0.94	0.93	0.88	0.84	1.18

Finally, in Table 3-3, from FHWA (Mallela & Sadavisam, 2011), shows the distribution of traffic in urban and rural areas throughout a typical weekday. Again, if a project manager seeks to minimize RUCs, it would be preferred to schedule active work zones during the early morning hours in both urban and rural situations to avoid active work zones operating during 0600 to 2059.

Table 3-3: Distribution of Daily Traffic by Time Interval

Time Interval	Urban (% of ADT)	Rural (% of ADT)
0000 – 0259	2.7	4.6
0300 – 0559	2.9	4.6
0600 – 0859	19.2	10.2
0900 – 1159	15.2	16.0
1200 – 1459	17.2	18.9
1500 – 1759	22.9	23.6
1800 – 2059	13.1	14.0
2100 – 2359	6.8	8.1

Referring back to natural diversion, the factors from Table 3-1, AADT, and the diversion factor found from simulation models can be applied to find the new expected traffic volume of the work zone using Equation 3.2

$$f_t(t) = \alpha_D(t)\left[\frac{f_t^*(t)}{\alpha_s}\right] \qquad \text{(Eq.3.2)}$$

Where:

$f_t(t)$ = Average traffic demand on the highway after the establishment of the work zone (*vehicles at time*, t),

$\alpha_D(t)$ = Diversion Factor (between 0 and 1, fraction of drivers who divert),

α_S = Seasonal Demand Factor (Table 3-1), and

$f_t^*(t)$ = Average traffic demand on the highway prior to the establishment of the work zone (*vehicles at time*, t)

This equation, modified from Karim's work (Karim & Adeli, 2003), provides a more accurate portrayal of work zone traffic demand than just using historic numbers. As up to 40 percent of commuters have been found to divert due to an incident (Khattak et al, 1994), this conversion should not be ignored readily. However, as the diversion factor requires previous work to determine (similar work zone traffic studies, or network analysis models), and varies with work zone delay, overestimating the RUCs presented in this thesis would be favorable to underestimation.

3.2 ROAD USER COSTS MODEL COMPONENTS

The RUC Model quantifies three avenues in which personal and freight vehicles are affected by delays in work zones: lost time costs, operating costs, and emission costs. Each component is outlined below. Note that all provided equations are direct modifications of current AASHTO and FHWA methodologies, unless otherwise noted.

3.2.1 Lost Time Costs

The first component of RUCs are costs due to personal and business time lost when travelers are delayed reaching their ultimate destination. The *Lost Time Cost (LTC)* for each vehicle class *c* that travels through a work zone (in dollars per vehicle) is calculated using Equation 3.3:

$$LTC_c = VoT_c \times O_c \times D \qquad \text{(Eq. 3.3)}$$

Where:

LTC_c = Lost Time Cost for vehicle class *c* (*dollars per vehicle*),

VoT_c = Value of Time for vehicle class *c* (*dollars per hour*),

O_c = Vehicle Occupancy of vehicle class *c* (*persons per vehicle*), and

D = Average Delay of the work zone (*hours*),

Values for these components are outlined below.

When calculating Total LTC for the work zone for the day, one will need to sum the individual LTC values for each vehicle type. As there are three vehicle classes outlined in this thesis (personal, single-unit freight, and combination freight), the calculation is generalized by multiplying the LTC value for each vehicle/purpose type with the number of vehicles that fall in that category and adding these sums.

Value of Time (VoT). It is well documented that individuals and freight experience different values of travel time (and therefore face different values of lost time due to delay). Table 3-4; based on values from AASHTO, FHWA, and the Bureau of Labor Statistics (AASHTO, 2010; Bureau of Labor Statistics, 2017; Mallela & Sadavisam, 2011); provides guidance on a range of values of travel time for passenger and freight vehicles under different trip purposes.

Table 3-4: Personal and Freight Values of Travel Time

Travel Purpose	Value of Time ($/hr)	
	PERSONAL VEHICLES	*FREIGHT VEHICLES*
General Personal (Local)	$12.91	--
General Personal (Intercity)	$18.07	--
General Work/Business	$30.97	$30.46
Transport & Warehousing	--	$28.10
Utilities	--	$46.39

Vehicle Occupancy (O). Vehicle occupancy can also vary by facility type and region. While states and metropolitan planning organizations are likely to have information specific to their region, Table 3-5 provides average vehicle occupancy for the different regions of the US if local information is unavailable. These rates are taken from Census Transportation Planning Products (CTPP) estimates of the American Community Survey 2006 – 2010 (Census Bureau, 2010). Refer to Table 6-1 for a table of states in each region.

Table 3-5: Average Vehicle Occupancy by Census Region

Census Region	Average Vehicle Occupancy	
	PERSONAL VEHICLES	*FREIGHT VEHICLES*
U.S. Overall	1.07	1.00
Northeast	1.06	1.00
Midwest	1.06	1.00
South	1.14	1.00
West	1.08	1.00

Average Delay (D). The average delay (*D*) used in the LTC equation is identified from the work zone analyzed. *D* can be measured by tracking vehicles through the work zone. It is important to recognize that *D* (in hours) measures the additional delay experienced by vehicles beyond the typical delay one would experience on the roadway without the presence of a work zone. Delay can be summed into two separate equations: one for detour scenarios, and one for lane closure/general delay. Below, detour delay can be calculated using Equation 3.4:

$$D_{Detour} = \left[\left(\frac{L_{Detour}}{S_{Detour}}\right) - \left(\frac{L_{Normal}}{S_{Normal}}\right)\right] \qquad \text{(Eq. 3.4)}$$

Where:

D_{Detour} = Detour delay time (*hours per vehicle*),

L_{Detour} = Detour length (*miles*),

S_{Detour} = Detour speed (*mph*),

L_{Normal} = Normal travel length (*miles*), and

S_{Normal} = Normal upstream speed (*mph*)

For situations where lanes of traffic are reduced and detours are not utilized, the delay function is divided into four distinct sections: delay due to deceleration, delay due to reduced speed, delay due to acceleration, and delay due to vehicle queues. Jiang's general delay equation for uncongested traffic conditions (Jiang, 2001) is calculated using Equation 3.5:

$$D = F_{ai}(d_d + d_z + d_a + d_w) \qquad \text{(Eq. 3.5)}$$

Where:

D = Delay time (vehicle hours),

F_{ai} = Average arrival rate of vehicles in hour i (*vehicles*),

d_d= Delay due to deceleration entering the work zone/queue (*hours*),

d_z= Delay due to work zone speed (*hours*),

d_a = Delay due to acceleration out of the work zone (*hours*), and

d_w = Average waiting time a vehicle spends before entering the work zone (*hours*)

Delay from acceleration, deceleration, and work zone speed are the easiest and most straightforward factors to calculate. The average arrival rate requires field studies to accurately predict, or by using the average hourly traffic (AHT). The average waiting time requires current field data to accurately measure as it varies by region, surrounding location (urban/rural/suburban), and work zone type. In addition, this equation is designed for uncongested traffic flow situations, which limits its application to mainly non-peak hours. For more information regarding general delay calculation for congested and uncongested traffic conditions, refer to Jiang's *Estimation of Traffic Delays and Vehicle Queues at Freeway Work Zones* (Jiang, 2001).

3.2.2 Operating Costs

The second component of RUCs are additional costs related to idling a vehicle during a work zone traffic delay, referred to as vehicle operating costs. Personal and freight vehicles incur typical operating costs every mile they travel, but when a work zone generates a detour or congestion, vehicles generate additional operating costs. According to AASHTO, these operating costs include fuel, maintenance, insurance, and registration costs of the vehicle; directly perceived out-of-pocket expenses (AASHTO, 2010). For work zone applications, current practice emphasizes the use of fuel costs.

Operating costs are calculated differently for personal and freight vehicles. The Operating Cost (OC) for the personal vehicle class traveling through a work zone (in dollars per vehicle) is calculated using Equation 3.6:

$$OC_{personal} = FC_{personal} \times D \times FP + OwnC_{personal} \times L \qquad \text{(Eq. 3.6)}$$

Where:

$OC_{personal}$ = Operating Costs for personal vehicles (*dollars per vehicle*),

$FC_{personal}$ = Fuel Consumption for personal vehicles (*gallons per hour*),

FP = Fuel Price (*dollars per gallon*),

D = Average Delay in the work zone (*hours*),

$OwnC$ = Ownership Cost of the vehicle (*dollars per mile*), and

L = Length of the work zone (*miles*)

Values for these components are outlined below.

Alternatively, FHWA (Mallela & Sadavisam, 2011) recommends the Operating Cost RUC (OC) for each freight vehicle *i* that travels through a work zone (in dollars per vehicle) follow the same function as above with an additional inventory cost based on delay shown in Equation 3.7:

$$OC_{freight} = \begin{cases} FC_{freight} \times D \times FP + 0.20 \times D & for\ Single\ Unit; 25{,}000 lb\ vehicles \\ FC_{freight} \times D \times FP + 0.34 \times D & for\ Combination; 42{,}000 lb\ vehicles \end{cases} \quad \text{(Eq. 3.7)}$$

Where:

$OC_{freight}$ = Operating Costs for freight vehicles (*dollars per hour*),

$FC_{freight}$ = Fuel Consumption for freight vehicles (*gallons per hour*),

D = Average Delay in the work zone (*hours*), and

FP = Fuel Price (*dollars per gallon*)

FHWA suggests hourly inventory costs of $0.20/hr for single-unit trucks (25,000 lb.) and $0.34/hr for combination trucks (42,000 lb.) when adjusted from 2010 to 2016 dollars.

When calculating Total OC for the work zone for the day, one will need to sum the individual OC values for each vehicle type. As there are only 3 vehicle types (personal, single unit freight, and combination freight) used in the calculation, one can simplify the calculation by multiplying the OC value for each vehicle type with the number of vehicles that fall in that category and adding these.

Fuel Consumption (FC). AASHTO evaluated a variety of vehicle fuel consumption rates (in gallons per hour) (AASHTO, 2010), and these are averaged in Table 3-6 for application in this thesis. These cost estimates assume the average car is retired after 75,000 miles. This is considered the average lifespan of a vehicle by AASHTO

Table 3-6: Fuel Consumption by Vehicle Type (gallons per hour)

Traffic Speed	Personal Vehicle (Gasoline Only)	Freight (Diesel Only)	
		SINGLE UNIT	*COMBINATION*
25	1.56	5.82	14.52
35	2.04	8.94	19.62
45	2.58	12.36	24.66
55	3.24	15.96	29.70
65	3.96	19.68	34.68
75	4.80	23.52	39.66

Fuel Price (FP). Fuel prices vary greatly and change frequently. For up-to date estimates, users should refer to the US Energy Administration for current fuel prices across different US regions.

Ownership Cost (OwnC). For every mile traveled, a vehicle will lose value and incur wear and tear. This factor summarizes these effects across a variety of vehicle types. AASHTO (AASHTO, 2010) provides a complete review of automobile operating ownership costs across small cars, midsize cars, large cars, SUVs and vans, as seen in Table 3-7. Values of freight could not be found. For this thesis, personal vehicle ownership costs are simplified to an average of $0.21 per mile.

Table 3-7: National Average Vehicle Ownership Costs (dollars per mile)

SMALL CAR	MIDSIZE CAR	LARGE CAR	SUV	VAN
$ 0.16	$ 0.196	$ 0.219	$ 0.253	$ 0.219

Average Delay (D). The average delay used in Equations 3.6 and 3.7 is identified from the work zone being analyzed. This value can be measured by tracking vehicles through the work zone. It is important to recognize that this delay measures (in hours) the additional delay experienced by vehicles beyond the typical travel time one experiences on the roadway without the work zone present. Refer to the previous section for details.

Length of Work zone (L). This is the defined length of the work zone in miles.

3.2.3 Emissions Costs

The third component of RUCs are incurred on the environment through air pollutants, such as carbon monoxide (CO) and particulate matter (PM2.5), as well as greenhouse gas emissions which include direct emissions that are not recognized as air pollutants but do contribute to global climate change (Mallela & Sadavisam, 2011). The presented methodology for this thesis is for static emissions costs. This method is not as detailed and accurate as dynamic emission costs, but allows for easy calculation. If a more detailed analysis is required, the current version of the EPA's Motor Vehicle Emission Simulator (MOVES) software is suggested for dynamic emissions calculations. It provides usable costs for all states except California which uses its state's software, California Emission Factors (EMFAC). MOVES can be used on a macro or micro-scale across multiple user-defined time aggregations (i.e. it can determine emissions on a per hour or a per month basis). What makes this model superior to static calculation methods is its inclusion of detailed emissions sources such as vehicle running, starting, extending idling, tire wear, brake wear, and general life cycle processes.

The static Emission RUC *(EC)* for each vehicle class *c* that travels through a work zone (in dollars per vehicle) is calculated using Equation 3.8:

$$EC_c = \sum^{P} ER_{pc} \times EC_{pc} \times L \times 0.00000110231 \qquad \text{(Eq. 3.8)}$$

Where:

EC_c= Emission RUC for each vehicle class *c* (*dollars per vehicle*),

ER_{pc} = Emission Rate of pollutant p for vehicle class *c* (*grams per mile*),

EC_{pc} = Emission Cost of pollutant p for vehicle class *c* (*dollars per ton*), and

L = Length of the work zone (*miles*)

The additional factor is a conversion between grams and tons. Values for these components are outlined below.

Emission Rate (ER). The values presented in Table 3-8 in grams per mile, are the 2017 aggregated estimates used by the California EMFAC model. Emissions included are CO, PM2.5, EPA-defined Volatile Organic Compounds (VOC) and Nitrogen Oxides (NOx). These values represent the average California emission rates across all tested model years with the "personal vehicle" category containing all passenger car models and the "freight" category describing all medium-heavy and heavy-heavy diesel trucks. Additionally, these values reflect running emissions and assume vehicles are moving through the work zone.

Table 3-8: EMFAC Model Emission Rates for Personal and Freight Vehicles (g per mile)

Traffic Speed	Personal Vehicle (Gasoline Only)				Freight (Diesel Only)			
	CO	*VOC*	*NOx*	*PM2.5*	*CO*	*VOC*	*NOx*	*PM2.5*
5	1.987	0.151	0.175	0.011	5.096	1.679	16.898	0.191
15	1.488	0.062	0.123	0.005	2.396	0.781	9.761	0.124
25	1.189	0.033	0.099	0.002	1.212	0.325	5.89	0.077
35	1.007	0.022	0.088	0.002	0.773	0.199	4.713	0.066
45	0.897	0.018	0.086	0.001	0.513	0.13	4.077	0.066
55	0.819	0.019	0.089	0.001	0.398	0.102	3.791	0.079
65	0.738	0.022	0.095	0.001	0.374	0.095	3.607	0.082

Emission Cost (EC). The general monetary costs for each emission type, from the Highway Economic Requirements System – State Version (HERS-ST) software, can be found in Table 3-9. These costs are adjusted from the year 2000 estimates using the BLS CPI Calculator and rounded to the nearest $50 increment, and they describe the economic costs of health impacts causes by emissions. The CPI values incorporate both actual and perceived health costs for average consumers (Church, 2016).

Table 3-9: Adjusted HERS-ST Emissions Costs by Surrounding Development

Development	Personal Vehicle (Gasoline Only)			
	CO	*VOC*	*NOx*	*PM2.5*
Urban	$150	$5850	$7650	$6800
Rural	$75	$3900	$5100	$3400

Length of Work Zone (L). This is the defined length of the work zone in miles.

For this thesis, the emissions cost equation can be simplified as Equation 3.9:

$$EC_c = EF_c \times L \qquad \text{(Eq. 3.9)}$$

Where:

EF_c = Combined Emission Factor for vehicle class c (*dollars per mile*), and

L = the defined length of the work zone (*miles*)

Emission Factor (EF). The values from the previous two tables are combined into Table 3-10. This table simplifies the EC calculation based solely on the vehicle type and location of the work zone.

Table 3-10: Summarized Emissions Costs per Mile

Traffic Speed **(mph)**	Personal Vehicle (Gasoline Only)		Freight (Diesel Only)	
	URBAN	*RURAL*	*URBAN*	*RURAL*
5	$0.0028604	$0.0018385	$0.1555966	$0.1033520
15	$0.0017205	$0.0010998	$0.0886732	$0.0588945
25	$0.0012592	$0.0008042	$0.0525418	$0.0348983
35	$0.0010654	$0.0006800	$0.0416490	$0.0276622
45	$0.0009971	$0.0006388	$0.0357978	$0.0237686
55	$0.0010159	$0.0006535	$0.0332840	$0.0220797
65	$0.0010725	$0.0006934	$0.0317057	$0.0210244

The emissions costs during construction will always be higher than pre-construction levels due to force flow conditions, accelerations, and queuing characteristics. Therefore, the proper course of action is to find the change between pre-construction and current work zone conditions calculated using Equation 3.10:

$$\Delta EC_c = EC_{c,work\ zone} - EC_{c,pre-construction} \qquad \text{(Eq. 3.10)}$$

Where:

ΔEC_c = Change in emissions cost during construction for vehicle class *c* (*dollars*),

$EC_{c,work\ zone}$ = Emissions Cost for vehicle class *c* based on work zone posted speed (*dollars*), and

$EC_{c,pre-construction}$= Emissions Cost for vehicle class *c* based on pre-construction posted speed (*dollars*)

Each separate EC value would be solved as outlined above with the only difference being the traffic speed. For example, if am urban roadway was to be subjected to a work zone calling for a drop in the posted speed limit from 55mph to 35mph, the $EC_{c,\ pre\text{-}construction}$ variable would refer to the "Traffic Speed: 55" row of Table 10 while the $EC_{c,\ work\ zone}$ variable would refer to the "Traffic Speed: 35" row.

3.3 COSTS CALCULATION EXAMPLE

Recalling the previous section, overall RUC calculation is a simple and straightforward process that involves summing all the specific user costs listed (i.e., lost time costs, operating costs, and emissions costs) and multiplying by associated traffic volumes using Equation 3.1:

$$RUC_i = LTC_i + OC_i + EC_i \tag{Eq. 3.1}$$

Where:

RUC_i = Road User Costs for vehicle i (*dollars per vehicle*),

LTC_i = Lost Time Cost for vehicle i (*dollars per vehicle*),

OC_i = Operating Cost for vehicle i (*dollars per vehicle*), and

EC_i = Emissions Cost for vehicle i (*dollars per vehicle*)

Since this equation is specific for one vehicle, results would need to be aggregated for each vehicle to determine the total RUC per day. From there, it is a simple equation of multiplying the daily user costs by the duration, in days, of the project. Granted, this method is only reliable for short construction periods and seasonal adjustments may need to be considered for projects lasting greater than six months.

To provide an example, let's say the following rehabilitation project is occurring on a 2-mile stretch of rural two-lane arterial in May. Table 3-11 shows the characteristics of the proposed project as well as several assumptions:

Table 3-11: Proposed Project Characteristics

CHARACTERISTIC	VALUE
LENGTH OF PROJECT	2 miles
PRE- CONSTRUCTION POSTED SPEED LIMIT	45 mph
AADT	4200 vehicles
DIVERSION FACTOR	0.8
WORK ZONE POSTED SPEED LIMIT	35 mph
ESTIMATED AVERAGE DELAY	10 minutes (0.167 hours)
TRUCK VOLUME (SU ONLY)	8%
PROJECT MONTH	May
DURATION OF PROJECT	10 Days
VALUE OF TIME (PERSONAL)	$12.91
VALUE OF TIME (FREIGHT)	$30.46
OCCUPANCY RATE (PERSONAL)	1.07
PRICE OF GASOLINE	$2.50
PRICE OF DIESEL	$2.90

The first step would be to determine the expected traffic volume as well as the expected number of personal vehicles and freight vehicles. The diversion equation (Equation 3.2) is applied:

$$f_t(t) = 0.8\left[\frac{4200\ vehs}{0.97}\right] \approx 3464\ vehs$$

The 0.97 factor is from Table 1 intersection of rural arterial and May, the 0.8 from the Table 11 diversion factor, and the 4200 vehicles is the AADT specified for the project. From this number, 8 percent of would be considered freight (277 vehicles) and the rest (3187 vehicles) would be considered personal vehicles.

The next step would be to determine the LTC, EC, and OC costs from Equations 3.3, 3.6, 3.7, 3.8, and 3.10. The LTC, EC, and OC costs for personal vehicles and freight are calculated below. Remember that EC is found from the difference of work zone and pre-construction emissions.

$$LTC_{Personal} = (\$12.91)(1.07)(0.167hrs) = \$2.31$$

$$OC_{Personal} = \left(2.04\frac{gal}{hr}\right)(0.167hrs)\left(^{\$2.50}/_{gal}\right)\left(^{\$0.21}/_{mile}\right)(2\ miles) = \$0.36$$

$$\Delta EC_{Personal} = [(\$0.00068)(2miles)] - [(\$0.00064)(2miles)] = \$0.00008$$

$$RUC_{Personal} = \$2.31 + \$0.36 + \$0.00008 = \$2.67\ per\ vehicle$$

$$LTC_{Freight} = (\$30.46)(1.00)(0.167hrs) = \$5.09$$

$$OC_{Freight} = \left(8.94\frac{gal}{hr}\right)(0.167hrs)\left(^{\$2.90}/_{gal}\right) + \left(^{\$0.26}/_{mile}\right)(0.167hrs) = \$4.37$$

$$\Delta EC_{Freight} = [(\$0.02766)(2miles)] - [(\$0.02377)(2miles)] = \$0.00779$$

$$RUC_{Freight} = \$5.09 + \$4.37 + \$0.00779 = \$9.48\ per\ vehicle$$

Using the RUCs and associated adjusted traffic volumes for each vehicle class, the total RUC per day is found to be roughly $11,132 for 3187 personal vehicles and 277 freight vehicles. This cost, multiplied by the duration of the project, results in a total RUC of $111,321 for this project. Since this is assuming a constant average delay for the project as well as the expected uniform traffic flow, it should be noted this predicted cost would be presented as a "ballpark" estimate as opposed to a precise measurement.

3.4 SUMMARY

Traditionally, RUCs have been divided into three main categories: LTCs, OCs, and ECs. This section presented accepted methodology used by AASHTO and FHWA as well as basic traffic volume distribution and modified traffic flow theory due to natural diversion. Existing methodology was adapted and updated in most cases for streamlined use and reliability. All associated monetary values were updated from 2000/2010 dollars to 2016/2017 dollars using related sources or the BLS CPI calculator. Additionally, vehicle classes were reduced to three unique types (personal, single unit freight, and combination freight). This was done once again to streamline the estimation process. Lost Time Costs were found to be the largest costs experienced by road users, followed by Operating Costs, then Emissions Costs. Although Emissions Costs were incredibly small, their calculation and value should not be ignored. Finally, it was found the largest influences of RUCs was delay time and traffic volume. As traffic volume was shown to be directly related to time of day, day of week, and delay time; it is of the utmost importance delay time is minimized to as minor as possible with work zone scheduling following suite.

CHAPTER 4: CRASH MITIGATION COSTS

In 2015, there were 96,626 recorded work zone crashes in the United States; averaging one crash every 5.4 minutes (Federal Highway Administration, 2017a). Although the crash severity distribution is similar for work zone and non-work zone crashes, work zone crashes have traditionally resulted in higher rates of fatalities. 2014 reports stated there were 669 fatalities recorded in work zones, equating to 2 percent of all national roadway fatalities (National Highway Traffic Safety Administration, 2015). 43 percent of these fatal crashes occurred on urban freeways and arterials, even though they only make up 5 percent of the total roadway mileage; an effect of higher AADTs. Additionally, rear-end crashes accounted for 43 percent of all fatal work zone crashes, compared to 16 percent of all fatal crashes. Therefore, continued research into work zone crash trends and factor identification is vital for crash reduction. Crash Mitigation Costs (CMCs) are the second of the three category impacts associated with roadway pavement rehabilitation work and quantified in this thesis. CMCs are defined as the cost associated with the most likely crash type to occur at a work zone. The FHWA and National Highway Traffic Safety Administration (NHTSA) have done countless reports and studies to evaluate the economic impact of crashes resulting in the KABCO scale (outlined below in Table 4-1). This scale designates 5 types of crashes that can occur within a work zone, on a severity scale from a property damage only crash (PDO) to fatal crash (K). Additionally, the typical cost associated with each crash type, including both direct and indirect costs, is reported in the Highway Safety Manual (Bonneson 2010). Table

4-1, from the Highway Safety Manual, has been scaled to 2016 dollars using the same methodology outlined in the previous chapter.

Table 4-1: Comprehensive Unit Costs by FHWA Severity Scale

Crash Severity CODE	Descriptor	Cost per Injury ($)
K	Fatal	4,008,900
A	Incapacitating Injury	216,000
B	Non-Incapacitating Injury	79,000
C	Possible Injury	44,900
PDO	Property Damage Only	7,400

This section calculates a Total Dollar ($) per Project Duration Crash Mitigation Cost for any given work zone based on the most likely crash to occur at the specified location. This chapter is organized as such: first, the data collection methods and associated summary characteristics are outlined; next, the crash model's methodology is discussed; following this, the model results and their interpretation are presented; finally, a simple example of how to use the results is shown.

4.1 DATA COLLECTION

The work zone crash type prediction model is based on representative work zone crash records. The data includes crashes from eight states (Alabama, California, Illinois, Maine, North Carolina, Ohio, Pennsylvania, and Washington) across the country, to ensure that the model is transferrable for work zones in any US region. Specifically, crash data was collected from three primary sources: a) the Highway Safety Information System (HSIS), b) the Alabama Department of Transportation work zone crash database compiled by Auburn University, and c) the PENNDOT OpenData Portal. Current crash records were collected from 2008 to the most recent year, which varied by state. The database across all states and years includes 4,324,686 total crashes and 89,212 work zone related crashes, roughly 2.1 percent. The specific number of total crashes from each state across each year are presented in Table 4-2. It is important to recognize that the crash records used in this analysis are generated by a law enforcement officer, who designated the location (i.e. in a work zone or not) of the crash and recorded the vital information.

Table 4-2: Work Zone Crashes Collected Across the United States

STATE	WORK ZONE CRASHES	PERCENT OF TOTAL WORK ZONE CRASHES
ALABAMA	4,840	5.4%
CALIFORNIA	20,300	22.8%
ILLINOIS	25,230	17.1%
MAINE	1,528	1.7%
NORTH CAROLINA	9,083	10.2%
OHIO	20,555	23.0%
PENNSYLVANIA	11,324	12.7%
WASHINGTON	6,352	7.1%
TOTALS	89,212	100.0%

Each crash includes many variables in addition to crash severity, including driver characteristics, crash characteristics, roadway characteristics, and project characteristics. Due to the range of data sources, all record variables were normalized to similar variable categories. Specifically, every record was restructured to match the North Carolina data dictionary, as it provided the most flexibility in variable definitions. A few states identified multiple at-fault persons in multiple-vehicle crashes, so the ages and genders for all the people at-fault in these crashes were combined in the record. This resulted in some crashes having several different age and gender categories when run through the final model so gender and age categories reflected all involved drivers instead of only at-fault drivers. Additionally, a few variables were either not present in each state's dataset or were not included in the responding officer's report. If this occurred, the variable was recorded as "other" or "unknown", as appropriate. Finally, any crashes showing an unknown KABCO variable were removed from the dataset to limit error in the final statistical model.

Initial analysis of the final data set showed that trends varied from national trends in most cases due to data availability. Regardless, Figure 4-1 shows the final work zone crash set broken down by census region.

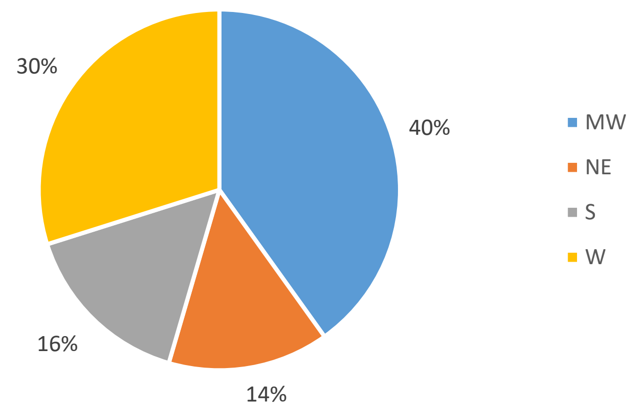

Figure 4-1: Work Zone Crashes by Census Region

In terms of population, the Midwest and West regions were overrepresented in the number of crashes (mainly due to California and Ohio data) with the South underrepresented due to the lack of available data. Efforts were made to acquire data from Texas and Florida since they, along with California, have the highest vehicle miles traveled of all the states, but were abandoned due to time constraints and communication issues.

Driver age was included for statistical comparison reasons. Figure 4-2 presents the data set categorized by driver age.

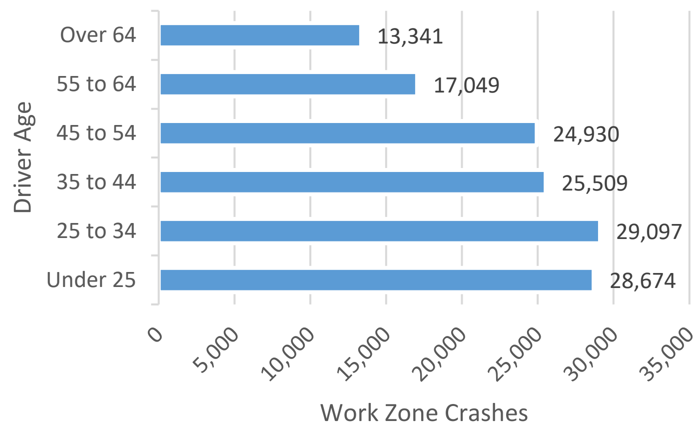

Figure 4-2: Work Zone Crashes by Driver Age

It should be noted that these numbers are based off all involved drivers since there was no way to determine the at-fault driver in most crashes. Regardless, crash trends proved to be similar to national trends in terms of driver age.

Figure 4-3 below presents the crash severity distribution of the final data set.

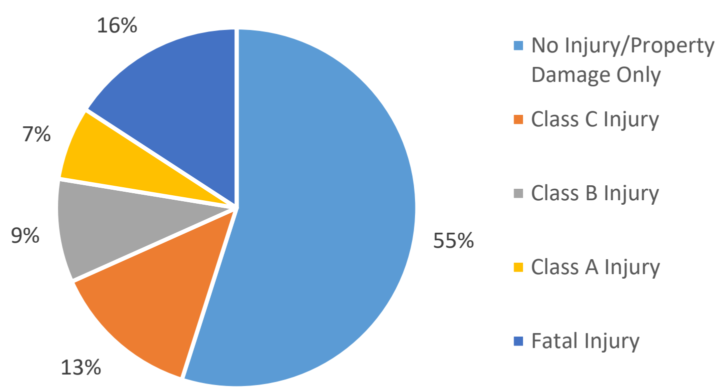

Figure 4-3: Work Zone Crashes by Severity Level

According to FHWA 2015 statistics, work zone crash severity levels were roughly summed up as 73 percent "PDO", 26.4 percent "Injury", and 0.7 percent "Fatal" (FHWA, 2017a). The working data set reflects these national trends in terms of general proportion except for fatal injuries. This was mainly due to the recording methods of some states, mainly Pennsylvania, where only fatal crashes were recorded with all the necessary roadway information needed for a full analysis. This overrepresentation of fatal crashes provides more data for a category that typically has less available data, which allows us to identify more detailed relationships and more accurately estimate the model. Table 4-3 shows the distribution of crash severity by involved driver age.

Table 4-3: Crash Severity by Driver Age [Percent of Severity (Standard Deviation)]

DRIVER AGE	K	A	B	C	PDO	TOTAL
UNDER 25	17.7% (0.73)	7.5% (0.10)	9.7% (1.69)	13.9% (1.42)	51.2% (-0.96)	100.0%
25 – 34	17.7% (0.73)	7.7% (0.48)	9.3% (-0.70)	13.5% (0.39)	51.8% (-0.71)	100.0%
35 – 44	17.2% (0.47)	7.7% (0.48)	9.3% (-0.70)	13.0% (-0.91)	52.8% (-0.29)	100.0%
45 – 54	16.9% (0.31)	7.7% (0.48)	9.6% (1.09)	12.8% (-1.42)	53.0% (-0.20)	100.0%
55 – 64	16.1% (-0.10)	7.8% (0.67)	9.3% (-0.70)	13.2% (-0.39)	53.6% (0.05)	100.0%
OVER 64	12.2% (-2.14)	6.3% (-2.20)	9.3% (-0.70)	13.7% (0.91)	58.5% (2.11)	100.0%
AVERAGE	16.3%	7.5%	9.4%	13.4%	53.5%	100.0%

As age increased, the proportion of PDO crashes increased and fatal crashes decreased. The largest deviations occurred with work zone crashes that involved drivers over the age of 64 years-old. Here, over two standard deviations from the mean were observed for fatal crashes (2.14 deviations less), Class A crashes (2.20 deviations less), and PDO crashes (2.11 deviations greater). Other notable trends included the increased chance of injury for involved drivers under 25 years-old. This was the only group to be consistently above the average injury rate for all four injury categories.

For this study, road surface composition was determined to be a vital component. Figure 4-4 shows the data set's breakdown by surface composition.

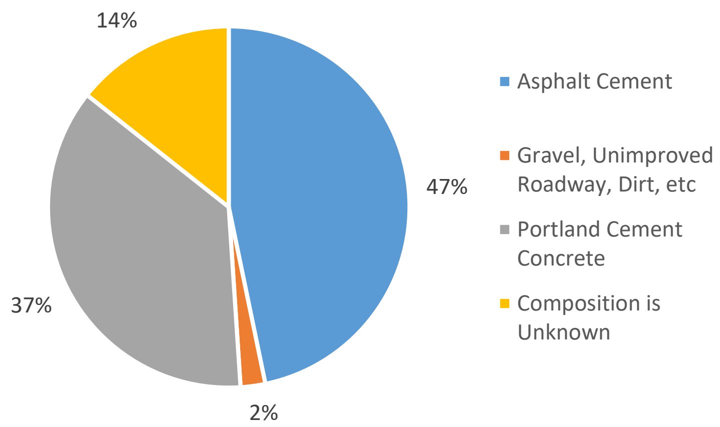

Figure 4-4: Work Zone Crashes by Surface Type

Effort was made to get an even sample of both AC and PCC crashes. According to FHWA reports, of the 4.1 million miles of roadway in the United States, over 783,000 miles are paved with AC while only 57,000 are paved with PCC (FHWA, 2017b). However, an additional 112,000 miles is defined as "composite", i.e. the application of an AC overlay over a jointed concrete pavement. The sizable sample of PCC crashes recorded could be related to the large number of recorded urban crashes where PCC application is more common (FHWA, 2017b). The large percentage of "unknown" cases was mainly due to incomplete reports, or in the case of the Alabama dataset, lack of an identifiable surface composition variable. Final model results would not be largely affected by this unknown presence since the model was designed for categorical dummy variables.

Other notable statistics included a 26/74 percent split rural/urban area definition, 82 percent of crashes occurring during clear weather, and 70 percent of crashes occurring during daylight lighting conditions. These further statistics reflected work zone crash trends found in previous studies by Kockelman, Bai, and Khattak (Bai, 2006; Khattak, & Council, 1998; Kockelman & Kweon, 2002); with the major exception of rural/urban split, as this was heavily influenced by study areas.

4.2 METHODOLOGY

The ordered probit regression model is the most appropriate method for predicting crash type because this dependent variable is a) categorical, meaning that crashes can only be labeled as one type, and b) presented in an ordered scale, meaning that the crash types move from low severity to high severity.

The ordered probit regression model is similar to a continuous linear regression model, in that it first calculates a continuous underlying unitless "likely crash severity" score for each work zone based on the input independent variables. This score has no upper or lower limits, but a higher score translates to a higher likelihood of a severe crash. The "likely crash severity" score equation can be calculated using Equation 4.1:

$$y^* = \beta' x + \epsilon \qquad \text{(Eq. 4.1)}$$

Where:

y^* = Injury severity level

β = Matrix of estimated coefficients

x = Matrix of independent variables

ε = Error term (assumed to be normally distributed)

Independent variables included traditional crash factors from past research describing driver characteristics, crash characteristics, roadway characteristics, and project characteristics. These are all categorical, indicator variables (for ease in application) with the exception of AADT and posted speed limit. The coefficients provide relative weights for each independent variable, assuming all other variables are held constant.

Next, the crash type categories are mapped to this underlying "likely crash severity" scale as demonstrated in Figure 4-5. One can see that the continuous "likely crash severity" score is partitioned into the scaled crash types, such that if a work zone receives a score between γ_3 and γ_4, the most likely crash type result is an "Incapacitating Injury". The thresholds between crash types are estimated specific for the model and do not need to be evenly spaced, highlighting the varying ranges of severity the can occur within each crash type. In the possibility of a threshold being statistically insignificant, it is interpreted as being as equally likely that a score could fall into either the insignificant threshold category or into a surrounding threshold category.

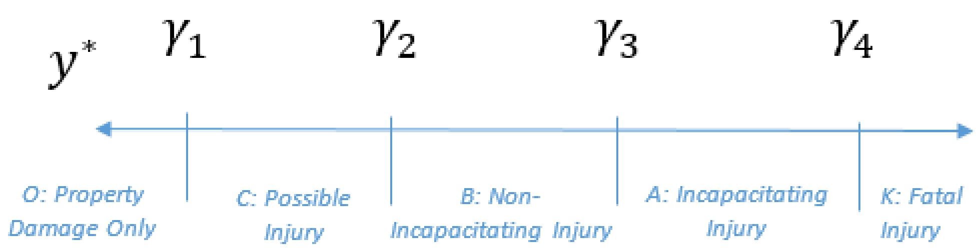

Figure 4-5: Likely Crash Severity Scale

This mapping can also be written as:

$$y = \begin{cases} K & if\ y^* > \gamma_4 \\ A & if \gamma_3 \leq y^* < \gamma_4 \\ B & if \gamma_2 \leq y^* < \gamma_3 \\ C & if \gamma_1 \leq y^* < \gamma_2 \\ O & if\ y^* \leq \gamma_1 \end{cases}$$

The ordered probit model assumes independence of irrelevant alternatives, low collinearity, and a normal distribution of error terms. This model is commonly used in crash severity analyses to identify factors affecting crashes. For example, Duncan used this method to determine injury severity level factors for heavy truck-passenger car rear-end collisions finding dark and wet roads greatly increased the probability of a severe injury (Duncan et al, 1998). Kockelman found through her research two-vehicle crashes had lower injury severities for their drivers as opposed to their passengers (Kockelman & Kweon, 2002).

The model coefficients and thresholds were estimated using maximum likelihood estimation. The model was iteratively estimated, removing variables that were insignificant at the 99 percent confidence level until a final model was derived. Model validity was tested using the chi-squared likelihood ratio. This ratio is the difference between the null (intercept-only) model's log likelihood value and the final (fitted) model's log likelihood value. If this value exceeds the critical chi-square value, then the null model is rejected. This is further demonstrated by the associating p-value which is the probability of obtaining the chi-square value with a model where all regression coefficients are set to zero. If the p-value is less than the alpha value ($\alpha = 0.01$), then the null hypothesis is rejected, stating the fitted model is better than the null model at a 99 percent confidence level.

4.3 ESTIMATION RESULTS AND DISCUSSION

Optimized model results produced the following threshold scale (Figure 4-6). All thresholds were found to be statistically significant allowing this model to be used to confidently predict a work zone's probable crash severity.

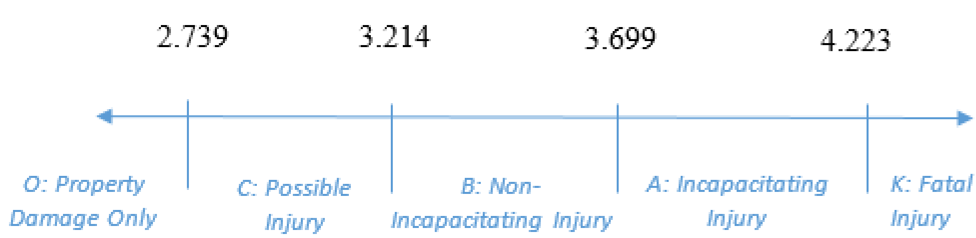

Figure 4-6: Work Zone Crash Severity Thresholds

To properly use this model, users must pair crash characteristics with its associated coefficient and sum the results. This summation would then be compared to the severity threshold ranges to determine the probable crash severity. The chi-squared likelihood ratio of the final model is 39034.15 with 32 degrees of freedom and a p-value of less than 0.001, confirming this model has a better fit than the null model. The final model estimation results are presented in Table 4-4. Dashes signify the variable, while tested, was not statistically significant in the final model.

Table 4-4: Work Zone Crash Severity Model Estimation Results

		IMPACT	
		COEFF.	***P-VALUE***
MODEL CHARACTERISTICS	Injury Thresholds		
	No Injury/Property Damage Only	< 2.739	
	Class C Injury (Possible Injury)	2.739	**< 0.001**
	Class B Injury (Non-Incapacitating Injury)	3.214	**< 0.001**
	Class A Injury (Incapacitating Injury)	3.699	**< 0.001**
	Fatal Injury	4.223	**< 0.001**
CRASH CHARACTERISTICS	**Weather (Base: Other)**		
	Clear	-	-
	Cloudy	-	-
	Rain	-0.333	**< 0.001**
	Snow	-0.548	**< 0.001**
	Census Region (Base: South)		
	Midwest	0.288	**< 0.001**
	Northeast	-	-
	West	1.525	**< 0.001**
	Season (Base: Winter)		
	Spring	-	-
	Summer	-0.048	**0.001**
	Fall	-0.059	**< 0.001**
	Time Of Week (Base: Weekend)		
	Weekday	-0.134	**< 0.001**

	Accident Type (Base: Other)		
	Ran Off Road	0.486	< 0.001
	Struck Object	0.256	< 0.001
	Rear-End	0.214	< 0.001
	Sideswipe	0.392	< 0.001
	Angle	0.216	< 0.001
	Driver Age (Base: Unknown)		
	Under 25	-	-
	25 To 34	-	-
	35 To 44	-	-
	45 To 54	-	-
	55 To 64	-	-
	Over 64	-0.057	< 0.001
ROAD CHARACTERISTICS	**Rural/Urban Locale**		
	Rural	0.240	< 0.001
	Urban	-	-
	Lighting (Base: Other)		
	Daylight	0.318	< 0.001
	Dusk	0.417	< 0.001
	Dawn	-	-
	Dark - Lighted Roadway	0.251	< 0.001
	Dark - Roadway Not Lighted	0.341	< 0.001
	Road Condition (Base: Other/Unknown)		
	Dry	-	-
	Wet	-0.114	< 0.001
	Ice/Snow	-	-
	Roadway Access (Base: Unknown)		
	No Access Control	0.194	< 0.001
	Partial Control	-0.855	< 0.001
	Full Control	-0.631	< 0.001
		-	-
	Roadway Classification (Base: Unknown)		
	Urban Freeways	-0.546	< 0.001
	Urban Freeways Less Than 4 Lanes	-0.733	< 0.001
	Urban 2 Lane Roads	-	-
	Urban Multilane Divided Non-Freeway	-	-

	Urban Multilane Undivided Non-Freeway	-	-
	Rural Freeways	-0.668	**< 0.001**
	Rural Freeways Less Than 4 Lanes	-	-
	Rural 2 Lane Roads	-0.313	**< 0.001**
	Rural Multilane Divided Non-Freeway	-	-
	Rural Multilane Undivided Non-Freeway	-	-
	Others	-	-
	Lane Width (Base: Unknown)		
	1 To 11 Feet	-0.432	**< 0.001**
	12 To 20 Feet	-0.503	**< 0.001**
	21 To 30 Feet	-	-
	Greater Than 30 Feet	-	-
	Surface Composition (Base: Unknown)		
	Asphalt Concrete	-0.188	**<0.001**
	Portland Cement Concrete	-	-
	Other	-0.185	**< 0.001**
	AADT (in 1000s Continuous)	0.003	**< 0.001**
	Speed Limit (Continuous)	0.051	**< 0.001**
	Likelihood Ratio Chi-Square	**39034.15**	**< 0.001**
	Degrees Of Freedom	**32**	

Although driver gender was found to be statistically insignificant in crash severity, driver age proved to be moderately influential. Drivers over the age of 64 were less likely to have a severe crash when all other factors were held constant. This can be explained by the crash severity distribution of the over 64 age group. As presented earlier, only 12.2 percent of crashes involving drivers over the age of 64 resulted in a fatality. This was found to be 2.14 standard deviations from the mean fatality rate of 16.3 percent. Previous research showed an opposite impact with an increase in age resulting in a higher chance of injury severity (Kockelman & Kweon, 2002). This could be due to methodology differences (continuous versus categorical variable) which would emphasize the larger driver population in the 21 to 55 age range.

Crash time and location played a significant part in determining crash severity. Tested western region states were the most likely states to have a higher severity work zone crash compared to all other census regions when all other factors were held constant. Since data used included California, the state's higher VMT counts could bias the results slightly to reflect the higher number of sever crashes. The Midwest region also showed a penchant for more severe crashes when all other factors were held constant. Once again, this could be due to the bias Ohio data presented with its large number of individual cases. Looking at surrounding locale classification, rural crashes were more likely to be severe than urban crashes when all other factors were held constant. Possible explanations for this could be the higher chances of two-lane, undivided highways that would increase head-on crashes if a lane was closed for rehabilitation.

Compared to all other unlisted weather events, rain and snow were the least likely to cause a more severe crash compared to the base category, when all other factors were held constant. While it is possible that there is a higher crash rate during these weather conditions, drivers could be operating at lower speeds, which would greatly reduce the severity level of an ensuing crash event. This is once again reflected under the road condition category where wet road conditions were less likely to cause a more severe crash compared to other conditions, when all other factors were held constant.

Regarding seasonality, it played an overall negative role in crash severity with summer and fall being the only statistically significant seasons found compared to winter. From the summary statistics, it was found 64 percent of all work zone crashes occurred during these two seasons, but frequency of road construction occurs during this time at a higher rate than winter and spring seasons resulting in a small bias. Weekdays (Monday through Friday) were less likely than weekends (Saturday and Sunday) when all other factors held constant. Since travel and work zone activity occurs more often during the week, these results are not surprising and are in line with conventional knowledge. As for light conditions, dusk light conditions, compared to all other options, had the highest probability for high severity crashes when all other factors held constant. This could be due to drivers being blinded by the sun; obscuring their vision and increasing crash rates. Dark, not-lighted highways, compared to all other options, had the second highest probability for high severity crashes when all other factors held constant. Reasons for this are obvious—drivers who can't see the road are more likely to be surprised by work zones in general. The same can be said for dark, lighted highways where the impact was still high but was statistically safer than unlit roadways. Roadway characteristics and crash type in general greatly influence probable severity outcomes. Higher AADT and posted speed limits resulted in higher likelihoods of a severe crash when all other factors were held constant. Non-access-controlled roads were more likely to have severe crashes than all other types, when all other factors were held constant. Possible reasoning could be due to vehicles entering the roadway at random resulting in possible more right-angle crashes occurring. Full and partial control were less likely to have high severity crashes when all other factors were held constant. This reflects previous research on the subject where controlling access points statistically lowers crash severities and crash frequencies overall (Gluck et al, 1999; Schultz et al, 2009). Oddly enough, partial control roads were statistically the least likely to increase accident severity. This could be due to access points being situated mainly at controlled intersections, but further research would be needed to determine the actual cause. For crash type, crashes that occurred under the "ran of road" and "sideswipe" categories had a higher chance of severity compared to "other" category when all other factors held constant. Compared to previous studies, "rollover" crashes were found to be the deadliest (Duncan et al, 1998; Kockelman & Kweon, 2002); but due to the small sample size (roughly 1 percent) of those types of crashes in the dataset, they were combined into the "other" category in analysis.

Finally, roadway classifications were considered. Both urban and rural freeways were less likely to have high severity crashes than all other categories when all other factors were held constant. This can be attributed to full access control on these roadways, which in turn increases overall safety. Rural two-lane roads were less likely to have high severity crashes when all other factors were held constant. The lower AADTs as well as the lower speeds on such roadways would reduce severe accidents (Harwood et al, 2000). In addition, since surface rehabilitation usually results in a lane closure, traffic would be forced to use a single lane alternating flow between traffic directions. Lane width was found to follow a pattern of larger widths resulted in less severe crashes when all other factors were held constant. Explanations for this could be attributed to the increased maneuver room for vehicles to avoid crashes.

4.3.1 Costs Calculation Example

To illustrate how the model results influence crash severity, assume the following scenario. A work zone crash occurs on a 55 mph, limited access, asphalt concrete 2-lane highway. The crash occurred during a rainy summer evening in rural Ohio resulting in an angle crash. Using this information, an equation predicting the probable severity can be found:

$$y = -0.048(If\ Summer) + 0.194(If\ No\ Access) - 0.333(If\ Raining) - 0.313(If\ Rural\ 2\ Lane) + 0.417(If\ Dusk) - 0.188(If\ Asphalt\ Concrete) + 0.285(If\ Midwest\ Region) + 0.216(If\ Angle\ Crash) + 0.24(If\ Rural) - 0.114(If\ Wet) + 0.051(Speed\ Limit)$$

It can be assumed that since it is a rural setting, the “rural 2 lane” and “rural” factors can be included in this equation. In addition. Since it is raining, it is safe to assume the road surface would also be wet. Calculated, the probable severity, *y*, would equal 3.164 or a “Class C” injury according to the scale.

4.4 SUMMARY

On average, a work zone crash occurs every 5.4 minutes according to FHWA. Although only 0.7 percent of work zone crashes result in a fatality, the estimated economic impact is in the millions. Therefore, it is imperative that efforts be made to reduce crash rates as well as severity levels. Using a nationally distributed crash database, an ordered probit model was developed to illustrate work zone crash severity thresholds as well identify influencing characteristics. Results showed the most statistically significant factor to be the posted speed limit and census region (specifically the Western census region). Although speed limit was found to be in accordance to past studies, the Western census region’s significance was thought to be the result of data set bias. Other notable results were wet weather conditions, weekday crashes, and drivers over the age of 64 causing less severe work zone crashes, compared to their bases and when all other factors were held constant. Rural two-lane roads were found to not impact crash severity as greatly as previous studies had found. However, both urban and rural freeways were found to be the least likely road type to cause a severe crash compared to all other road type categories. Finally, work zone crashes that occurred at dusk were the most likely lighting category to cause a severe crash compared to all other lighting categories—although this was not found in previous studies, where unlit dark road conditions were found to lead to the most severe crashes.

CHAPTER 5: LOCAL BUSINESS IMPACT COSTS

Local Business Impact Costs (LBICs) are the third of the three categories of impacts associated with roadway pavement rehabilitation work and quantified in this thesis. LBICs are defined as the economic impacts on local businesses from nearby pavement rehabilitation work zones caused by changes in customer spending and visitation behaviors. As previous literature has shown, work zone delay can result in motorists changing their habits based on the theory of natural diversion and an individual's value of time. Additionally, previous work has shown perceived monetary losses to businesses have in general been higher than actual losses. This results in negative connotations between business owners and road owners leading to unnecessary conflict (Buddemeyer et al, 2008). Despite being a well-documented challenge, there is little guidance on how engineers should quantify these impacts. Therefore, a national survey was conducted to determine customer preferences to different work zone durations as it related to their activity choices. Results were gathered from an ordered probit model with direct monetary relations taken from the survey response distributions. First, a summary of data collection and summary statistics is presented. Following this, an explanation of the ordered probit model is provided. Finally, model results and variable explanations are discussed.

5.1 DATA COLLECTION

The national LBIC survey was conducted through the Survey Monkey platform to limit costs and maximize the sample size. Originally, 425 responses were recorded then another 345 responses were solicited during the ensuing phases. Respondents were chosen to reflect US Census demographics and socioeconomic factors to allow a representative sample of the entire nation. Questions covered consumer spending habits among three different activities (leisure, grocery shopping, home/houseware shopping), average travel times to said activities, and behavioral changes to travel if a work zone of variable durations is introduced to the trip. Respondents were asked how an increased travel time of 5, 20, or 40 minutes over a project duration of a day, week, or month would affect their travel choices. Respondents were provided five choices:

- "Still take the trip."
- "Reschedule the trip for another day/time while construction is still happening and the delay is still the same."
- "Reschedule the trip for another day/time after construction is completed and there is no longer a delay."
- "Go somewhere else."
- "Cancel trip entirely (including shopping online instead)."

Additionally, the scenarios included either a duration for the work zone construction of either a day, a week, or a month. These durations were assigned probabilistically across all respondents, meaning that each scenario had a 1/3 chance of being assigned one of these durations and the overall entire sample of scenarios included an equal distribution of all three durations.

This was asked for each of the three activity categories with construction duration distributed at a 33 percent probability. Overall, 770 survey responses were recorded before cleaning.

Since the survey was conducted electronically, all results were already formatted into an easy-to-use SPSS file so little cleaning/formatting was required. Even with mandatory responses and incentives to complete the survey, 55 of the original respondents (7 percent) did not complete the survey in some form or another and had their responses removed from the final dataset. Final model results were calculated using the final 715 sample size.

Each respondent was asked several demographic questions to not only identify second-round survey target response groups, but to also put results into context. Figure 5-1 shows the age distribution of respondents.

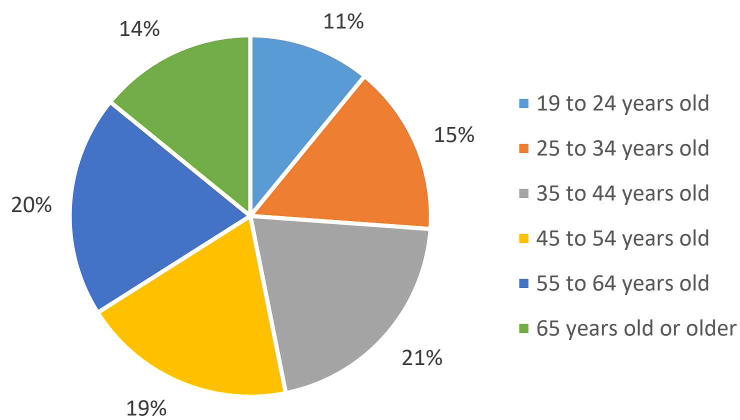

Figure 5-1: Age Distribution of Sample

Due to Institutional Research Board (IRB) regulations, all respondents had to be 19 years of age or older to take the survey, but these categories were still matched to crash results in the previous section. Compared to US Census 2015 estimates (Census Bureau, 2016), the “35 to 44 years old” and “55 to 64 years old” categories were overrepresented by roughly 8 percent each, and the “45 to 54 years old" category was overrepresented by roughly 5 percent. However, the "19 to 24 years old" and "65 years old or older" categories were within a percent of actual representation.

Respondent gender (Figure 5-2), although not accounted for in the crash results, reflected national trends within ±5 percent.

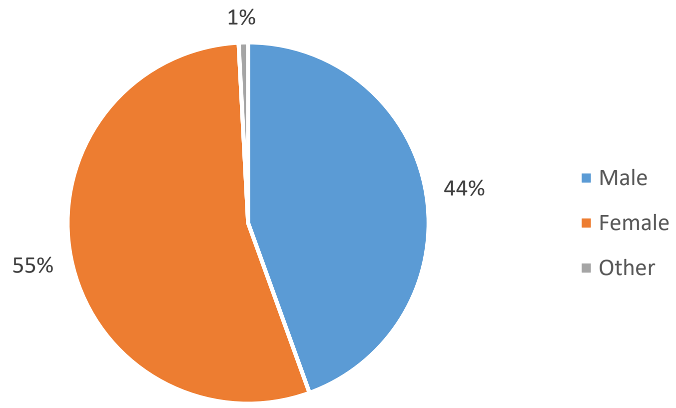

Figure 5-2: Gender Distribution of Sample

According to 2015 American Community Survey estimates, the US population is almost evenly split at 49 percent male and 51 percent female (Census Bureau, 2015). Regardless, these results were favorable.

Regionally, shown in Figure 5-3, survey results showed an almost perfect match to census estimates for 2016 with variations under ±1 percent (Census Bureau, 2016). Refer to Appendix B for a table of states in each region. Use of US Census region definitions was decided as the easiest way to describe the data in a nationally recognized scale. The individualization of states was deemed too detailed and complex for the scale of this project.

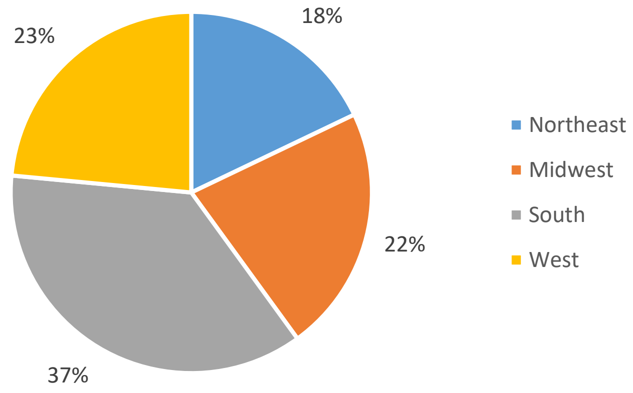

Figure 5-3: Regional Distribution of Sample

Household income, Figure 10, varied from census estimated data. While for household type, Figure 5-4, no records on matching national categories could be found.

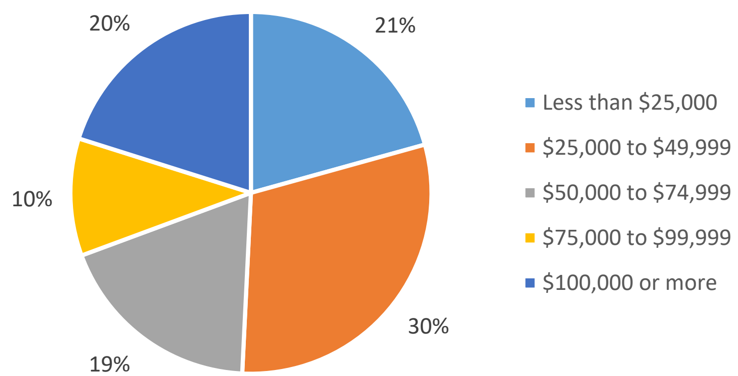

Figure 5-4: Income Distribution of Sample

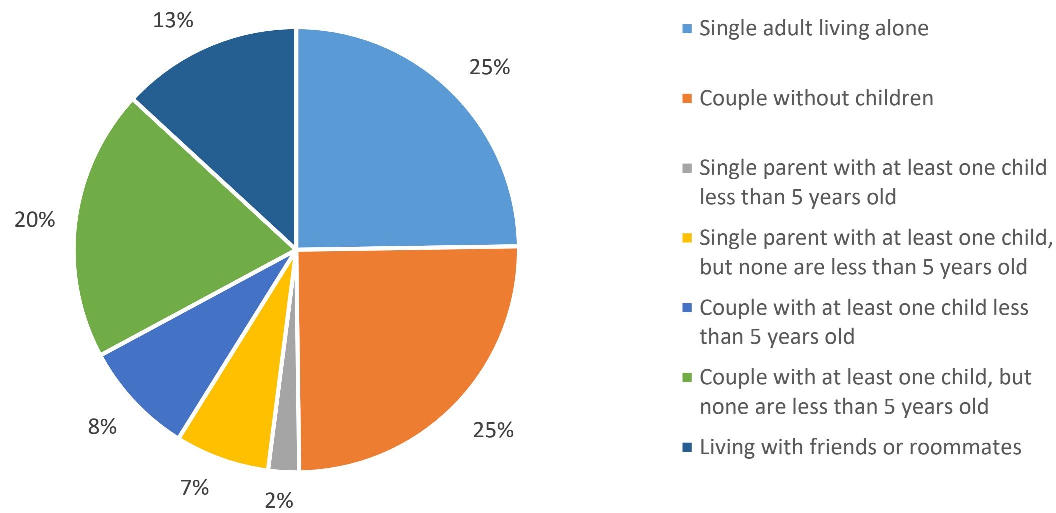

Figure 5-5: Household Type Distribution of Sample

Household income varied from the national estimates the most with the "$25,000 to $49,999" category at 6.5 percent over the national percentage (Census Bureau, 2015). All other categories were within ±3.5 percent of the national percentage. This tight grouping was considered the most important category to match for the model. As buying power is directly correlated to household income, the validity of the model depended on matching the national census estimates as closely as possible.

Overall, the highest proportion of survey respondents were 35 to 44-year-old, female, lived either alone or with children, lived in the Southern US region, or had household incomes in the $25,000 to $49,999 range. Conversely, the lowest proportions were survey respondents who identified as "other", 19 to 24 years-old, lived alone with children under the age of 5, lived in the Northeast region, or had household incomes in the $75,000 and $99,999 range. In the analysis, these infrequent choices would be used as the base cases in the model.

5.2 SURVEY RESULTS REGARDING USER DELAY

The most notable initial result was survey respondents' behavior choices for each delay category. For all business types tested (leisure, grocery, and personal shopping), there was a substantial shift between delay increases. Presented in Figures 5-6 through 5-8, most respondents, regardless of work zone duration, shifted their travel choice from "Still take the trip" to "Go somewhere else" when faced with a work zone delay exceeding 20 minutes.

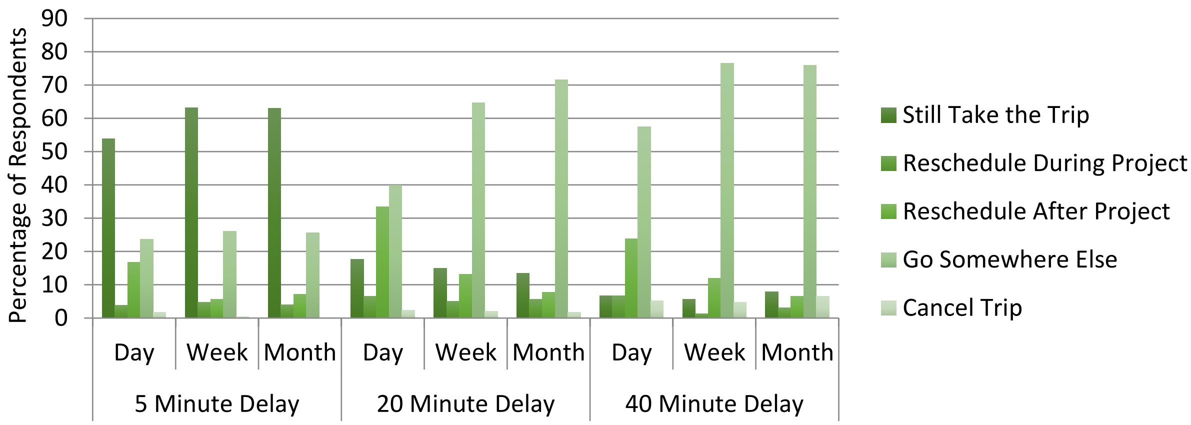

Figure 5-6: Survey Responses to Delay Increases for Grocery Trips

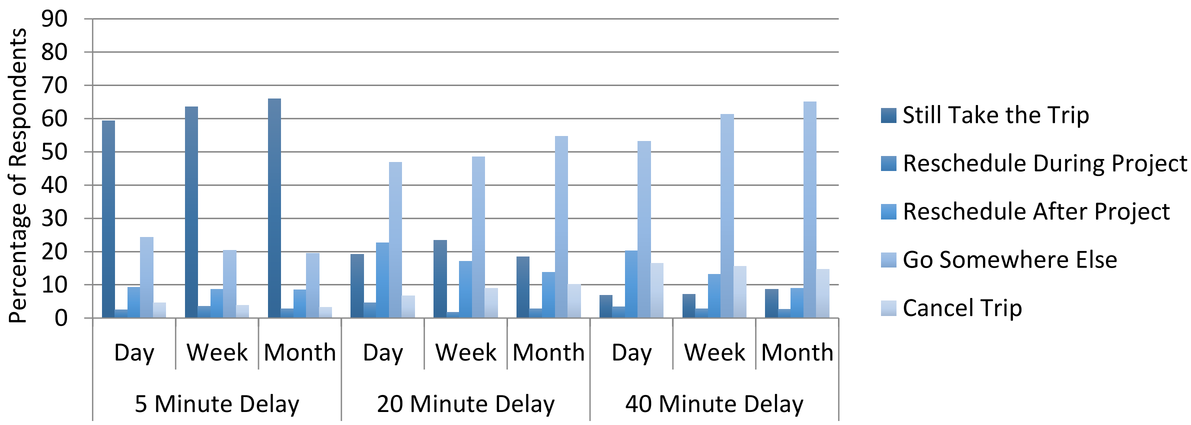

Figure 5-7: Survey Responses to Delay Increases for Leisure Trips

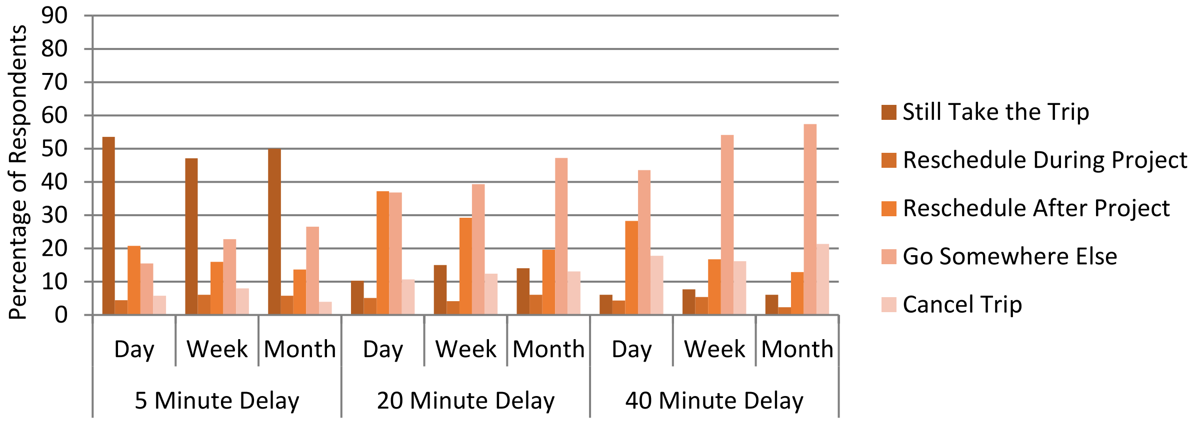

Figure 5-8: Survey Responses to Delay Increases for Personal Shopping Trips

Interestingly, leisure and personal shopping trips, compared to grocery trips, had a higher percentage of respondents who chose to cancel their trip entirely, across all delay types. This suggested respondents treated grocery trips as more essential than the other trip types. Regardless, overall results showed that somewhere between a delay time of 5 minutes and 20 minutes there is a significant shift in behavior. Previous research would suggest that the critical time would be around 15 minutes based on user VoT (Pinjari & Bhat, 2006), but further investigation is required to confirm.

5.3 METHODOLOGY

Again, the ordered probit regression model is the most appropriate method for predicting choice because this dependent variable is a) categorical, meaning that choices about whether to take the trip or not are mutually exclusive, and b) presented in an ordered scale, meaning that the choices move from 'no deviation from regular behavior' to a 'complete change in behavior'.

The ordered probit regression model is similar to a continuous linear regression model, in that it first calculates a continuous underlying unitless "trip disruption/aggravation" score for driver that travels through a work zone based on the input independent variables. This score has no upper or lower limits, but a higher score translates to a more likely deviation from the original travel. This "trip disruption/aggravation" score equation can be calculated using Equation 5.1:

$$y^* = \beta' x + \epsilon \qquad \text{(Eq. 5.1)}$$

Where:

y^* = Injury severity level

β = Matrix of estimated coefficients

x = Matrix of independent variables

ε = Error term (assumed to be normally distributed)

Independent variables describe driver characteristics, region characteristics, roadway characteristics, and project characteristics. These are all categorical, indicator variables (for ease in application). The coefficients provide relative weights for each independent variable, assuming all other variables are held constant.

Next, the driver trip choice categories are mapped to this underlying "trip disruption/aggravation" scale as demonstrated in Figure 5-9. One can see that the continuous "trip disruption/aggravation" score is partitioned into the scaled trip decisions, such that if a driver receives a score between γ_3 and γ_4., the most likely outcome would be for the driver to "go somewhere else". The thresholds between trip decisions are estimated specific for the model and do not need to be evenly spaced, highlighting the varying ranges of annoyance/impact that work zones that can occur within each avoidance behavior type. In the possibility of a threshold being statistically insignificant, it is interpreted as being as equally likely that a score could fall into either the insignificant threshold category or into a surrounding threshold category. In the case of strict application, the level of insignificance can be ignored.

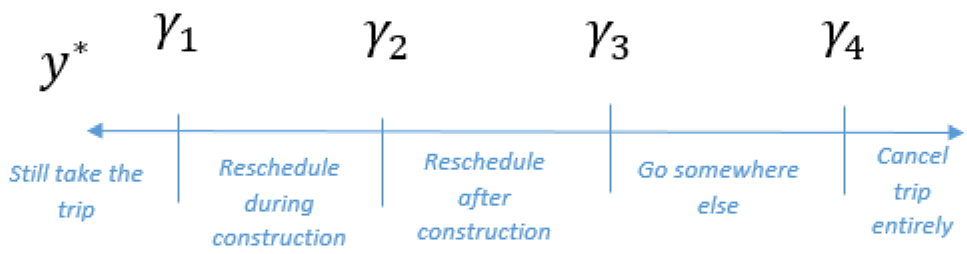

Figure 5-9: Trip Distribution/ Aggravation Scale

This mapping can also be written as:

$$y = \begin{cases} Cancel\ trip\ entirely & if\ y^* > \gamma_4 \\ Go\ somewhere\ else & if \gamma_3 \leq y^* < \gamma_4 \\ Reschedule\ for\ after\ construction & if \gamma_2 \leq y^* < \gamma_3 \\ Reschedule\ during\ construction & if \gamma_1 \leq y^* < \gamma_2 \\ Still\ take\ the\ trip & if\ y^* \leq \gamma_1 \end{cases}$$

The ordered probit model assumes independence of irrelevant alternatives, low collinearity, and a normal distribution of error terms. The model coefficients and thresholds were estimated using maximum likelihood estimation. The model was iteratively estimated, removing variables that were insignificant at the 99 percent confidence level until a final model was derived. Model validity was tested using the chi-squared likelihood ratio. This ratio is the difference between the null (intercept-only) model's log likelihood value and the final (fitted) model's log likelihood value. Log likelihood values improve the closer they converge to zero. If this ratio value exceeds the critical chi-square value, then the null model is rejected. This is further demonstrated by the associating p-value which is the probability of obtaining the chi-square value with a model where all regression coefficients are set to zero. If the p-value is less than the alpha value ($\alpha = 0.01$), then the null hypothesis is rejected, stating the fitted model is better than the null model at a 99 percent confidence level.

5.4 ESTIMATION RESULTS AND DISCUSSION

Optimized model results produced the following threshold scale (Figure 5-10). All thresholds but those highlighted red were found to be statistically significant. With the highlighted thresholds, motorists are equally as likely to either still take the trip or reschedule it at another time during construction. Participants most likely assumed that work zone delay would be less if they went at a different time during construction.

Grocery	**0.914**	**1.219**	**2.024**	**6.292**
Personal	**0.363**	**0.685**	**1.832**	**4.100**
Leisure	**1.298**	**1.492**	**2.255**	**5.076**

Figure 5-10: LBIC Threshold Results (Red signifies statistical insignificance)

Threshold range varied by business category heavily between response choices. From observation, it appeared leisure trips had a higher threshold for changing from the base action, but was just as equally sensitive for change up to the third threshold. Each business category showed the threshold between "Go Somewhere Else" and "Cancel Trip Entirely" was over double or triple the previous threshold. This suggests respondents would prefer heavily to still take the trip, albeit to a different venue, than completely cancel plans—unless faced with extreme situations. The chi-squared likelihood ratios of the final models are 8825.68 for grocery, 4524.86 for personal shopping, and

5389.36 for leisure with all having p-values less than 0.001, confirming each model has a better fit than their associated null model. To properly use this model, users must pair their socioeconomic and work zone characteristics with its associated coefficient and sum the results for whichever business type is to be examined. This summation would then be compared to the response threshold ranges to determine the probable motorist response. The final model estimation results are presented in Table 5-1.

Table 5-1: Business Impact Model Estimation Results

		Impacts on Business Type…					
		Grocery Shopping		**Personal Shopping (e.g. Clothes or Home Goods)**		**Leisure Activity (e.g. Eat at a Restaurant or Go to a Movie)**	
		Coeff.	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*
Model Characteristics	**Choice Thresholds**						
	Still Take the Trip	< 0.914		< 0.363		< 1.298	
	Reschedule during construction	0.914	0.073	0.363	0.189	1.298	< 0.001
	Reschedule after construction	1.219	0.017	0.685	0.013	1.492	< 0.001
	Go somewhere else	2.024	< 0.001	1.832	< 0.001	2.255	< 0.001
	Cancel trip entirely	6.292	< 0.001	4.100	< 0.001	5.076	< 0.001
Region Characteristics	**US Region (Base: Northeast)**						
	West	0.271	0.012	-	-	-	-
	Midwest	-	-	-	-	-	-
	South	-	-	-	-	-	-
	Community Type (Base: Rural)						
	Urban	0.331	0.015	-	-	-0.230	0.062
	Suburban	0.289	0.014	-	-	-0.262	0.016

Driver Characteristics	**Age (Base: 19 to 24 years old)**						
	25 to 34 years old	0.742	< 0.001	-	-	-	-
	35 to 44 years old	0.836	< 0.001	-	-	-	-
	45 to 54 years old	0.745	< 0.001	-	-	0.559	< 0.001
	55 to 64 years old	0.391	0.024	-	-	0.564	< 0.001
	65 years old or older	0.599	0.002	-	-	0.550	< 0.001
	Gender (Base: Female)						
	Male	-	-	-	-	-	-
	Other	-1.076	0.028	0.828	0.063	-	-
	Household Type (Base: Single Adult)						
	Single Parent with at least one child less than 5 years old	0.582	0.063	-	-	-	-
	Single Parent with at least one child, none less than 5 years old	-	-	-	-	-	-
	Couple without children	0.227	0.045	-	-	0.203	0.054
	Couple with at least one child less than 5 years old	-	-	0.263	0.082	0.565	0.001
	Couple with at least one child, none less than 5 years old	-	-	0.332	0.003	-	-
	Living with Friends or Roommates	0.268	0.066	-	-	-	-
	# Household Vehicles (Base: 0 vehicles)						
	1 Vehicle	0.616	0.001	0.309	0.001	0.792	< 0.001
	2 Vehicles	0.672	< 0.001	-	-	0.654	< 0.001
	3 to 5 Vehicles	1.054	< 0.001	0.229	0.042	0.776	< 0.001
	6 or More Vehicles	1.924	0.034	-2.114	0.014	-2.669	0.021
	Household Income (Base: Less than $25,000)						
	$25,000 to $49,999	-	-	0.366	0.002	-	-
	$50,000 to $74,999	0.206	0.077	0.500	< 0.001	-	-
	$75,000 to $99,999	-	-	0.651	< 0.001	-	-
	$100,000 or more	-	-	0.610	< 0.001	-	-
	Typical Daily Commute (Base: 5 Minutes or Less)						
	6 to 10 minutes	-	-	-	-	-	-
	11 to 20 minutes	-	-	-	-	-0.287	0.005
	21 to 40 minutes	-	-	-	-	-	-
	41 to 60 minutes	-	-	-	-	-0.562	< 0.001
	Longer than an hour	-	-	-	-	-0.366	0.091

Business Activity Characteristics	**Typical Time to Reach Business (Base: 5 Minutes or Less)**						
	6 to 10 minutes	0.471	< 0.001	0.736	< 0.001	-	-
	11 to 20 minutes	0.478	< 0.001	1.119	< 0.001	-	-
	21 to 40 minutes	0.451	0.015	1.136	< 0.001	0.207	0.043
	41 to 60 minutes	-	-	1.562	< 0.001	0.529	0.006
	Longer than an hour	-1.883	0.002	0.704	0.048	-	-
	Typical Amount Spent at Business (Base: Nothing)						
	$1 to $20	-1.840	< 0.001	-0.732	0.009	-	-
	$21 to $50	-1.599	< 0.001	-0.993	< 0.001	-	-
	$51 to $100	-1.747	< 0.001	-1.255	< 0.001	-	-
	$101 to $200	-1.868	< 0.001	-1.218	< 0.001	-	-
	More than $200	-1.697	< 0.001	-1.399	< 0.001	-1.183	0.001
Construction Characteristics	**Construction Delay (Base: Minor [+5 minutes])**						
	Average [+20 minutes]	1.924	< 0.001	1.512	< 0.001	1.791	< 0.001
	Significant [+40 minutes]	2.660	< 0.001	2.140	< 0.001	2.550	< 0.001
	Construction Duration (Base: Day)						
	Week	0.366	0.001	-	-	-	-
	Month	0.476	< 0.001	0.238	0.006	0.217	0.014
	-2 Log Likelihood	*4407.79*	*< 0.001*	*4524.86*	*< 0.001*	*4001.47*	*< 0.001*
	Pearson Chi-Squared Ratio	*8825.68*	*< 0.001*	*5537.91*	*< 0.001*	*5389.36*	*< 0.001*

Regional characteristic results showed only grocery trips were statistically affected by which US Census region, West, the respondent was located. As for the respondent's community, both grocery and leisure trips were statistically significant. Urban and suburban respondents were more likely to change their grocery trip plans when faced with construction compared to rural respondents when all other factors were held constant. Leisure trips showed an opposite trend where urban and suburban respondents were less likely to change trip plans compared to rural respondents. As grocery shopping can be deemed more mandatory than leisure trips, rural respondents, most likely limited in grocery store options, would be less inclined to reschedule or cancel a trip. However, as leisure trips could be perceived as more of a luxury or abundant in options, rural respondents could be more willing to change trip plans.

Respondent demographics presented the most opportunities to influence trip-making decisions. Age categories showed a general trend of older age groups were less likely to change grocery and leisure trip plans compared to all other age groups. This could be the result of older individuals being less willing to change routines than younger individuals as illustrated in several studies (Agahi et al, 2006; Atchley, 1989, 1993). Gender results showed respondents who identified as "other" were less likely to change grocery trip plans, but more likely to change personal shopping trip plans compared to female respondents when all other factors were held constant. This is most likely the result of the small sample size of "other" respondents (roughly 1 percent) which could cause bias in the results. Household type showed influence over all three trip types in varying degrees. Only two categories ("Couple without children", and "Couple with at least one child less than 5 years old") were statistically influential over more than one trip type. Overall, households defined as having at least one child less than 5 years old, regardless of marriage status, were the most likely to change trip plans compared to all other household types. The number of household vehicles available had the most variety in influence statistically affecting all trip types over almost every single category. Respondents were more likely to change grocery trip plans as the number of vehicles available increased. However, leisure and personal shopping trips showed a rather odd inverse. As the number of household vehicles increased, the likelihood to change personal shopping trips decreased before greatly declining at the "6 or more" category. Leisure trips showed a steadier response, but once a respondent reached the "6 or more" category, the same inversion occurred; albeit at a greatly increased affect. Reasons for this could not be immediately ascertained.

Oddly enough, as the number of household vehicles could be an indicator of household wealth, household income did not reflect similar results. As household income increased, generally, the more likely a respondent was to change personal shopping trip plans. This could be an indicator of being able to afford more options therefore changing personal shopping locations would not be as detrimental.

Response results to business activity showed that as travel time increased for grocery trips, the less likely respondents were to change trip plans when all other factors were held constant. As grocery trips can be defined as the most mandatory of the three trip types defined in the survey, respondents would be less likely to change trip plans. Personal shopping and leisure trips showed opposite trends with respondents being more likely to change plans the longer the travel time. The only exception to this was personal shopping trips that took longer than hour to make. This could be the result of extreme rural isolation where options are severely limited; the same with grocery trips. Surprisingly, the amount of money typically spent at all trip types had a little affect in changing a respondent's mind in changing their trip plans, when all other variables were held constant. While grocery trips were uniform in coefficient weight, personal shopping showed a more negative trend as the amount spent increased.

Finally, construction characteristics showed that delay time was greatly more influential than the duration of the project. For all trip types, as delay time increased, respondents were inclined to change their trip plans when all other factors were held constant. This factor was so influential that average delay (+20 minutes) resulted in a base threshold of "rescheduling after construction" while significant delay (+40 minutes) placed a base threshold of "go somewhere else" when all other factors were held constant. To visualize, consider Figure 5-11:

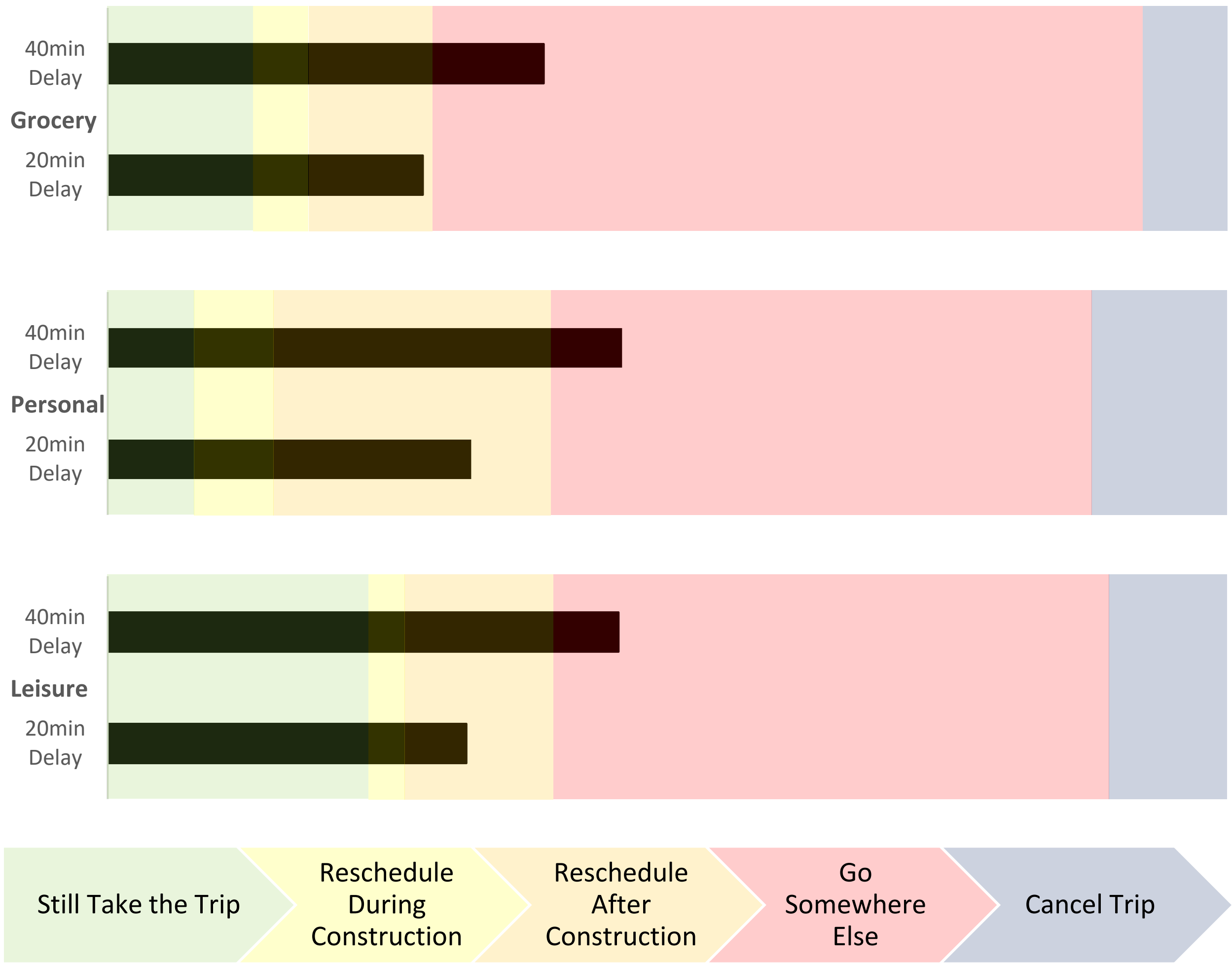

Figure 5-11: Effects of Work Zone Delay on Respondent Behavior

These charts show the corresponding thresholds passed for each activity and work zone delay type, when all other model factors are set to the base alternative. As shown, each activity exhibits different ranges for thresholds, with each colored zone representing the most probable respondent behavior. Using this information, it would be beneficial to limit work zone delay to as little as possible and to schedule construction at non-peak times to reduce traffic affected.

5.5 SUMMARY

During work zone rehabilitation projects that result in user delay, Local Business Impact Costs can be described as the most directly perceived costs of the three impact categories presented. Although a well-documented challenge, engineers and decision makers have been provided little guidance on how to predict and quantify these costs on a national scale. Using a nationally tailored stated preference survey and the ordered probit regression model, motorist response to work zone delays was quantified through socioeconomic, demographic, and work zone characteristics. Results showed work zone delay had the highest influence on trip choice with several socioeconomic and demographic characteristics (household income, trip travel time, and age) influencing trip choice in accordance to previous studies. Trip choice thresholds also varied by business type with leisure trips having the highest base threshold for behavior change. Additionally, the thresholds between “Go Somewhere Else” and “Cancel Trip Entirely” were double or triple the previous threshold. This suggests respondents would only cancel trips under the most unideal conditions.

CHAPTER 6: PAVEMENT REHABILITATION PROJECT COST TOOL

The three models are combined into a transferrable and easy-to-use Excel tool. This section outlines the tool interface, how users may implement the tool, a description of the tool's methodology, and suggestions on how utilize during construction project planning.

6.1 TOOL OVERVIEW

The tool is designed to provide U.S. users the ability to calculate costs associated with a rehabilitation project, regardless of their past modeling experience. As such, the tool only requires users to collect and enter information about the roadway, surrounding area, and work zone. The spreadsheet then calculates the impact costs once the user clicks the "calculate" button. The calculations run in the background are outlined in the next section.

It is important to recognize that the tool generates a simulated population of drivers through a work zone that reflect the distributions of regional population demographics. Each time the tool is used, it generates a new simulated set of drivers, which may provide slightly different LBIC results.

The tool has population distributions built-in to represent the four regions of the United States (Northeast, South, Midwest, and West), shown in Figure 6-1, that are generated from the 2010 US Census socioeconomic and demographic information. A detailed list of states in each region is provided in Table 6-1.

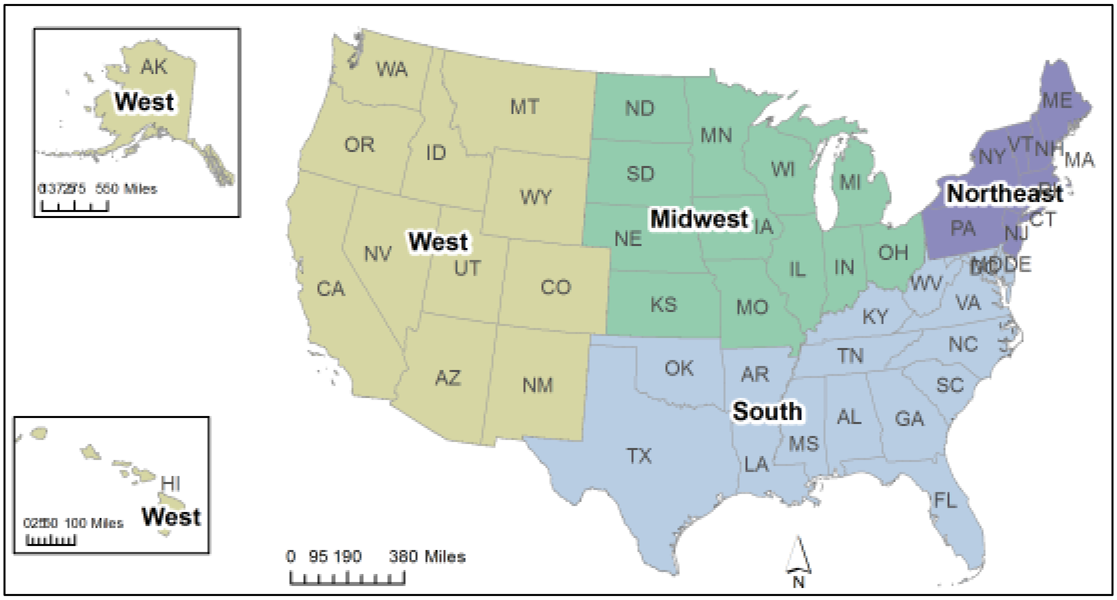

Figure 6-1: US Census Bureau Definitions of Demographic Regions

Table 6-1: US Census Bureau Demographic Region Categories

Northeast	**Midwest**	**South**	**West**
Connecticut	Illinois	Alabama	Alaska
Maine	Indiana	Arkansas	Arizona
Massachusetts	Iowa	Delaware	California
New Hampshire	Kansas	District of Columbia	Colorado
New Jersey	Michigan	Florida	Hawaii
New York	Minnesota	Georgia	Idaho
Pennsylvania	Missouri	Kentucky	Montana
Rhode Island	Nebraska	Louisiana	Nevada
Vermont	North Dakota	Maryland	New Mexico
	Ohio	Mississippi	Oregon
	South Dakota	North Carolina	Utah
	Wisconsin	Oklahoma	Washington
		South Carolina	Wyoming
		Tennessee	
		Texas	
		Virginia	
		West Virginia	

Users are limited to these base data sets for simulating drivers. However, local values for some inputs, such as gasoline and diesel prices, are allowed.

The Excel Workbook consists of five tabs: "Work Zone Characteristics", "Vehicle Simulation", "Regional Demographics", "Crash Costs", and "Reference Tables". Only the "Work Zone Characteristics" tab requires data input to use the tool effectively; the other tabs illustrate the methodology and statistics used to compute the end results. This section provides an overview and brief explanation of each tab.

6.1.1 Work Zone Characteristics

This is the main tab of the tool where all inputs and outputs are shown. All inputs can be entered via user input or selected via drop-down box. Figure 6-2 below, shows the layout.

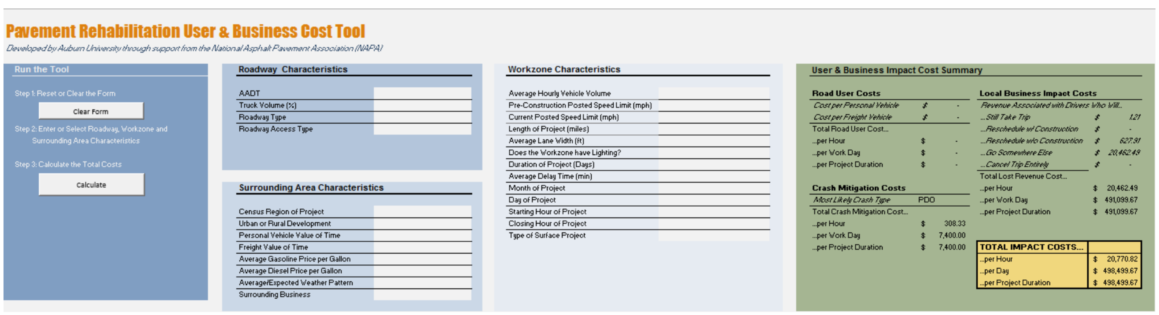

Figure 6-2: Cost Tool Overview

The user will spend most, if not all their time on this tab, so understanding it is key. The inputs required are divided into the three sections as illustrated in Figure 6-3.

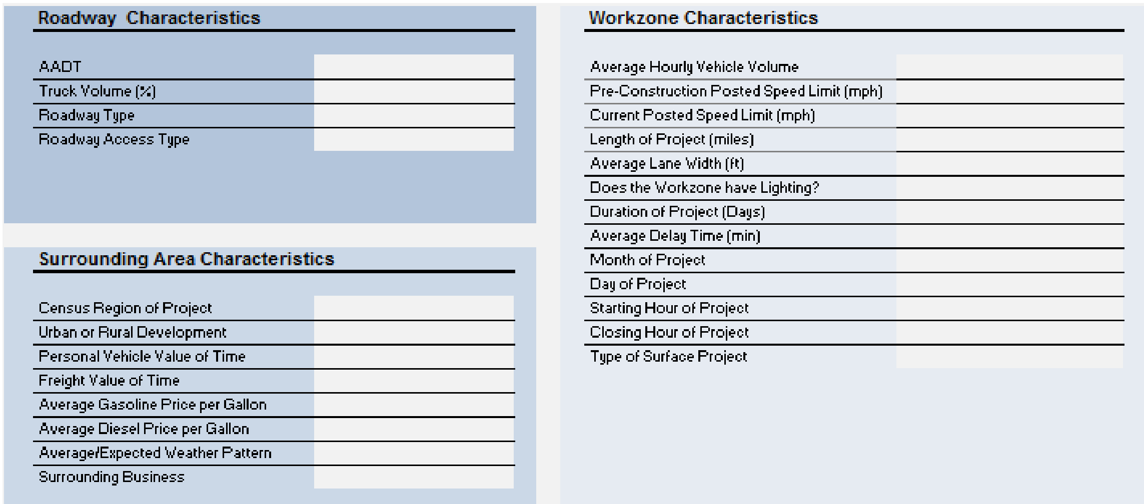

Figure 6-3: Variable Inputs

Users have 25 characteristics to describe a work zone across three different categories. Most inputs are determined via drop-down menus, including posted speed limit, so users are limited to certain scenarios. The variables needed to run the model are shown in Tables 6-2 through 6-4.:

Table 6-2: Roadway Characteristics

INPUT	INPUT TYPE	DESCRIPTION	WHERE TO FIND
AADT	User-Defined	Annual Average Daily Traffic	State DOT agency database
TRUCK VOLUME	User-Defined	Percent of AADT that is freight vehicles	State DOT agency database
ROADWAY TYPE	Drop-Down List	Roadway classification as defined by DOT	State DOT agency database
ROADWAY ACCESS TYPE	Drop-Down List	How traffic access is managed onto the roadway	State DOT agency database

Table 6-3: Surrounding Area Characteristics

INPUT	INPUT TYPE	DESCRIPTION	WHERE TO FIND
CENSUS REGION	Drop-Down List	Target state's US Census Region designation	US Census map provided
URBAN OR RURAL DEVELOPMENT	Drop-Down List	If project is located in a rural or urban area	Site visits, US Census designations
PERSONAL VEHICLE VALUE OF TIME	Drop-Down List	The value of time of the average personal vehicle	Provided
FREIGHT VALUE OF TIME	Drop-Down List	The value of time of the average freight vehicle	Provided
AVERAGE GASOLINE PRICE PER GALLON	User-Defined	Area average gasoline price per gallon	Site visits, AAA website
AVERAGE DIESEL PRICE PER GALLON	User-Defined	Area average diesel price per gallon	Site visits, AAA website
EXPECTED WEATHER PATTERN	Drop-Down List	Average weather conditions expected	Site visits, weather forecasts
SURROUNDING BUSINESS TYPE	Drop-Down List	Defines area business as leisure, personal, or grocery	Google Maps, surveys, site visits

Table 6-4: Work Zone Characteristics

INPUT	INPUT TYPE	DESCRIPTION	WHERE TO FIND
AVERAGE HOURLY VEHICLE VOLUME	User-Defined	Average number of vehicles while work zone is present	Onsite counts, AADT conversion using percentages from Table 3
PRE-CONSTRUCTION SPEED LIMIT	Drop-Down List	Normally posted speed limit	Site visits
WORK ZONE SPEED LIMIT	Drop-Down List	Posted speed limit during construction	Site visits, traffic plans
LENGTH OF PROJECT	User-Defined	Total length of the work zone in miles	Work zone plans
AVERAGE LANE WIDTH	Drop-Down List	Lane width of the travel-way	Site visits, Google Earth
WORK ZONE LIGHTING?	Drop-Down List	Is an artificial light source present for roadway illumination?	Site visits, work zone plans
DURATION OF PROJECT	User-Defined	How many full days the project is expected to last	Work zone plans
AVERAGE DELAY TIME	User-Defined	The average delay time expected in minutes	Site visits, estimates, traffic plans
MONTH OF PROJECT	Drop-Down List	The starting month of the project resulting in delays	Work zone plans
DAY OF PROJECT	Drop-Down List	The starting day of the project resulting in delays	Work zone plans
STARTING HOUR OF THE PROJECT	Drop-Down List	The starting hour of the project resulting in delays	Work zone plans
CLOSING HOUR OF THE PROJECT	Drop-Down List	The closing hour of the project ending delays	Work zone plans
TYPE OF SURFACE	Drop-Down List	The majority surface type used in the project	Work zone plans

In addition, a benefit of the tool is the limited inputs required to create a report. At a minimum, the average hourly vehicle volume and average delay time are required to produce a predicted Road User Cost. Obviously, the more information provided, the more accurate the results. Several assumptions, Table 6-5 are made for the tool to function properly:

4 *Table 6-5: List of Tool Assumptions*

TOPIC	ASSUMPTION
GENERAL	If the starting and ending time if the project is not specified, it is assumed the project duration is 24 hours.
	The value of time for personal vehicle and freight is assumed to be uniform for all road users.
	The average hourly wage and compensation for personal users are assumed to be $25.81 per hour and $30.46 per hour, respectively.
BUSINESS IMPACT COSTS	All vehicles are attempting to utilize the specified business.
	Only one business type can be selected at a time.
	Time of day is not factored into the calculation.
CRASH MITIGATION COSTS	Driver's age is 35 to 44 years old.
	If the specified weather pattern is "rain" or "snow", the road condition will be assumed to be "wet" or "ice/snow", respectively.
	The default crash type is assumed to be Property Damage Only (PDO).
	Only one of the most probable crash type determined will occur during the project duration.

5

As the user selects their inputs, the output section will automatically populate with the expected impact costs, shown in Figure 6-4.

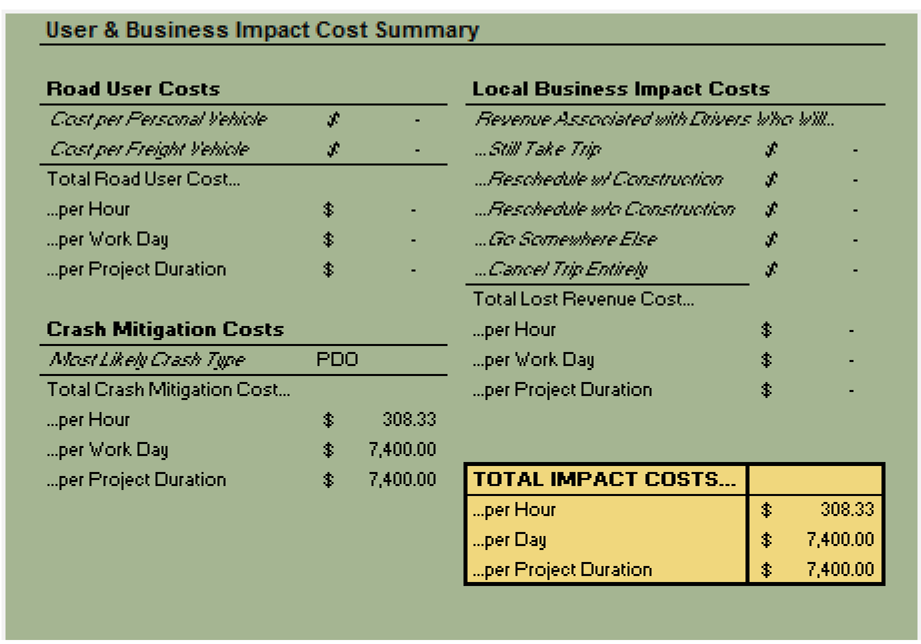

Figure 6-4: Tool Outputs

The probable impact costs are displayed to the user by hour, day, total project duration among each of the sections. It should be noted the tool assumes at least one crash will occur regardless, so the default is assumed to be “Property Damage Only”. Additionally, the LBIC section will not begin to populate until the “Calculation” button is pressed by the user. This is because the tool must use an Excel macro code to compute this section through a Monte Carlo simulation, explained in detail in the next section.

6.1.2 Vehicle Simulation Tab

This tab displays the results of each simulated vehicle used to determine the probable business impact costs. Using user input and regional-specific census demographics, simulated vehicles are created via a Monte Carlo simulation of the Business Impacts Model. Figure 6-5 shows an example output of the simulation.

SIMULATED VEHICLES

Simulated Vehicle	Business Type	Age	Gender	Household Type	# Vehicles	Income	Daily Commute	Access Time	Amount Spent
1	Leisure	45 to 59	Male	Couple w/ Children under 18	2 personal vehs	$25,000 - $49,999	10 -19 min	41 to 60 min	$51 - $100
2	Leisure	25 to 34	Female	Single Alone	1 personal veh	$25,000 - $49,999	20 - 39 min	11 to 20 min	$1 - $20
3	Leisure	60 to 64	Male	Single Alone	0 personal vehs	>= $100,000	20 - 39 min	6 to 10 min	$1 - $20
4	Leisure	25 to 34	Male	Single Alone	2 personal vehs	$75,000 - $99,999	20 - 39 min	11 to 20 min	$21 - $50
5	Leisure	Under 25	Male	Couple No Children	1 personal veh	$75,000 - $99,999	20 - 39 min	11 to 20 min	$0
6	Leisure	45 to 59	Male	Couple w/ Children under 18	3 to 5 personal vehs	$75,000 - $99,999	>59 min	11 to 20 min	$21 - $50
7	Leisure	35 to 44	Female	Single Alone	1 personal veh	$50,000 - $74,999	10 -19 min	6 to 10 min	$101 - $200
8	Leisure	45 to 59	Male	Single Alone	2 personal vehs	<$25,000	5 - 9 min	11 to 20 min	$51 - $100
9	Leisure	35 to 44	Male	Single Parent w/ Children under 18	1 personal veh	$25,000 - $49,999	10 -19 min	11 to 20 min	$21 - $50
10	Leisure	45 to 59	Male	Couple No Children	1 personal veh	$50,000 - $74,999	5 - 9 min	Less than 5 min	$21 - $50
11	Leisure	Under 25	Female	Couple No Children	2 personal vehs	<$25,000	5 - 9 min	11 to 20 min	$51 - $100
12	Leisure	45 to 59	Male	Couple No Children	2 personal vehs	$75,000 - $99,999	20 - 39 min	21 to 40 min	$21 - $50
13	Leisure	25 to 34	Female	Couple w/ Children under 18	2 personal vehs	>= $100,000	5 - 9 min	Less than 5 min	$21 - $50
14	Leisure	35 to 44	Male	Single Parent w/ Children under 18	2 personal vehs	$25,000 - $49,999	20 - 39 min	6 to 10 min	$21 - $50
15	Leisure	45 to 59	Female	Couple No Children	3 to 5 personal vehs	$75,000 - $99,999	20 - 39 min	11 to 20 min	$1 - $20
16	Leisure	60 to 64	Male	Single Alone	1 personal veh	>= $100,000	20 - 39 min	11 to 20 min	$51 - $100
17	Leisure	Under 25	Female	Living w/ Roommates/Friends	2 personal vehs	$50,000 - $74,999	20 - 39 min	Less than 5 min	$51 - $100
18	Leisure	35 to 44	Female	Single Alone	3 to 5 personal vehs	$25,000 - $49,999	20 - 39 min	21 to 40 min	$1 - $20
19	Leisure	35 to 44	Male	Living w/ Roommates/Friends	3 to 5 personal vehs	$50,000 - $74,999	10 -19 min	21 to 40 min	$51 - $100
20	Leisure	65 or older	Female	Living w/ Roommates/Friends	1 personal veh	$25,000 - $49,999	10 -19 min	11 to 20 min	$1 - $20

Figure 6-5: Monte Carlo Simulation Results

To the right of this section, the associated coefficient of the simulated vehicle is displayed as well as the resultant probable choice and costs. As a default, 1000 simulated vehicles are computed with their choices and associated monetary costs summed and computed into a probable distribution. This distribution is then scaled to the user-specified average hourly vehicle volume. This process is illustrated below in Figure 6-6.

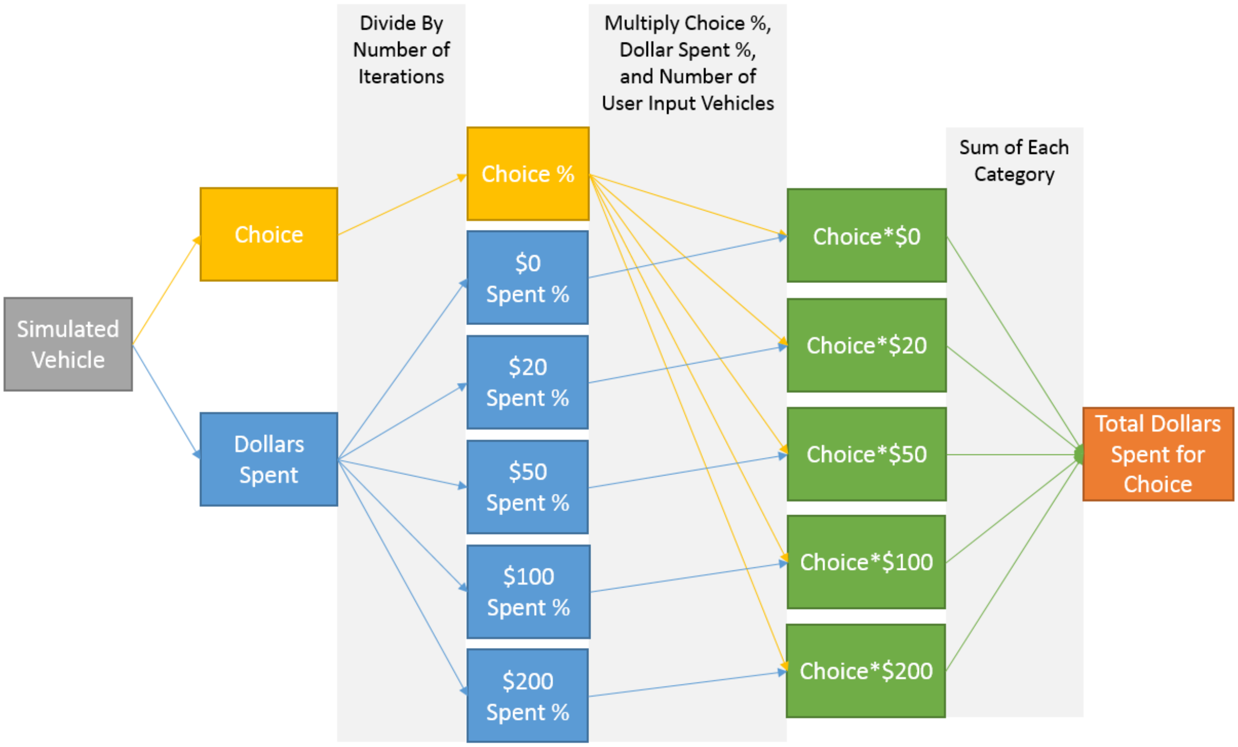

Figure 6-6: Scaling Procedure for Vehicle Simulation[1]

6.1.3 Regional Demographics Tab

This tab displays the census data characteristics used for the vehicle simulation section. Two tables are presented, a cumulative demographics table and the raw US Census Region Demographics table. This is purely for the tool to easily relate random probabilities back to actual distributions. There is no discrepancy between the values between the two tables.

---

[1] This illustration demonstrates the process for any one of the five probable choices a vehicle can make. By doing this, the deviation between run iterations is reduced to give the end user a more reliable predicted monetary impact.

6.1.4 Crash Costs Tab

This tab illustrates the crash characteristics pulled from the user inputs. Characteristics are identified by a binary system with a "1" signifying the applied characteristic coefficient. Results of this tab are relayed back to the output section of the "Work zone Characteristics" tab.

6.1.5 Reference Table Tab

All tables presented in the main report are displayed here for reference values. These tables are divided into four sections: Value of Time Tables, Operating Costs Tables, Time Modifier Tables, and Emission Cost Tables. Values from these tables are used by the tool to calculate the per hour, per day and project duration impact costs. They also allow the user to see where the values are being pulled from and offer an expanded selection of some of the tables presented in this thesis.

6.2 HOW TO USE THE TOOL

To operate this tool, the user needs to follow these three steps:

1. Reset or Clear the Form by pressing the "Clear Form" button located on the far right of the "Work Zone Characteristics" tab.
2. Enter or select Roadway, Work Zone, and Surrounding Area Characteristics via the input boxes.
3. Calculate the Total Costs by pressing the "Calculate" button located on the far right of the "Work Zone Characteristics" tab.

It should be noted that the "Clear Form" button DOES NOT reset the vehicle simulation used in the Local Business Impact Costs section. The vehicle simulation automatically resets each time the "Calculate" button is pressed by the user.

To demonstrate, let the following conditions exist for a work zone as shown in Figure 6-7:

Roadway Characteristics

AADT	15000
Truck Volume (%)	5%
Roadway Type	Two Lane Road (Arterial)
Roadway Access Type	No Control

Surrounding Area Characteristics

Census Region of Project	Midwest
Urban or Rural Development	Urban
Personal Vehicle Value of Time	General Personal (Intercity)
Freight Value of Time	General Work/Business
Average Gasoline Price per Gallon	$ 3.20
Average Diesel Price per Gallon	$ 3.20
Average/Expected Weather Pattern	Clear
Surrounding Business	Leisure

Workzone Characteristics

Average Hourly Vehicle Volume	625
Pre-Construction Posted Speed Limit (mph)	55
Current Posted Speed Limit (mph)	45
Length of Project (miles)	2
Average Lane Width (ft)	12 to 20 Feet
Does the Workzone have Lighting?	Yes
Duration of Project (Days)	8
Average Delay Time (min)	40
Month of Project	June
Day of Project	Tuesday
Starting Hour of Project	6:00 AM
Closing Hour of Project	5:00 PM
Type of Surface Project	Asphalt Concrete

Figure 6-7: Work Zone Example

Once the inputs are set as shown, the “Calculate” button is pressed to complete the results section. As the program is running, the user will see the impact costs begin to rise and summate with the other impact costs that were automatically calculated. Figure 6-8 below shows the final impact cost results.

User & Business Impact Cost Summary

Road User Costs		
Cost per Personal Vehicle	*$*	*21.87*
Cost per Freight Vehicle	*$*	*46.81*
Total Road User Cost...		
...per Hour	$	14,445.51
...per Work Day	$	158,900.56
...per Project Duration	$	1,271,204.49

Crash Mitigation Costs		
Most Likely Crash Type	PDO	
Total Crash Mitigation Cost...		
...per Hour	$	84.09
...per Work Day	$	925.00
...per Project Duration	$	7,400.00

Local Business Impact Costs		
Revenue Associated with Drivers Who Will...		
...Still Take Trip	*$*	*-*
...Reschedule w/ Construction	*$*	*-*
...Reschedule w/o Construction	*$*	*9.36*
...Go Somewhere Else	*$*	*36,545.09*
...Cancel Trip Entirely	*$*	*-*
Total Lost Revenue Cost...		
...per Hour	$	36,545.09
...per Work Day	$	401,995.99
...per Project Duration	$	3,215,967.91

TOTAL IMPACT COSTS...		
...per Hour	$	51,074.69
...per Day	$	561,821.55
...per Project Duration	$	4,494,572.40

Figure 6-8: Leisure Example Results

As you see, this work zone scenario had a total monetary impact of almost $4.5 million during its eight-day duration. It should be noted that the business impact costs are only for leisure activities. If we were to change the Surrounding Business Type to “Grocery” the following results may occur (Figure 6-9).

User & Business Impact Cost Summary

Road User Costs		
Cost per Personal Vehicle	*$*	*21.87*
Cost per Freight Vehicle	*$*	*46.81*
Total Road User Cost...		
...per Hour	$	14,445.51
...per Work Day	$	158,900.56
...per Project Duration	$	1,271,204.49

Crash Mitigation Costs		
Most Likely Crash Type	PDO	
Total Crash Mitigation Cost...		
...per Hour	$	84.09
...per Work Day	$	925.00
...per Project Duration	$	7,400.00

Local Business Impact Costs		
Revenue Associated with Drivers Who Will...		
...Still Take Trip	*$*	*0.12*
...Reschedule w/ Construction	*$*	*0.51*
...Reschedule w/o Construction	*$*	*0.94*
...Go Somewhere Else	*$*	*57,149.77*
...Cancel Trip Entirely	*$*	*-*
Total Lost Revenue Cost...		
...per Hour	$	57,149.77
...per Work Day	$	628,647.51
...per Project Duration	$	5,029,180.06

TOTAL IMPACT COSTS...		
...per Hour	$	71,679.37
...per Day	$	788,473.07
...per Project Duration	$	6,307,784.56

Figure 6-9: Grocery Example Results

Although some road users would still shop, the clear majority would still go somewhere else. Additionally, as people tend to spend more money on groceries compared to leisure trips, the overall impact costs has risen by nearly $1.8 million. Therefore, an alternative work zone design should be investigated to minimize these costs.

6.3 HOW TO APPLY THE TOOL

The tool can be applied in three significant ways:

6.3.1 Project Evaluation

First, the tool can characterize the road user, crash mitigation, and local business impacts of an existing project or projects that are being let for bid. For example, road owners can use the tool to conduct benefit-cost analyses based on their proposed plan, scheduling, material choices, work zone layout, etc. This information can put construction costs in perspective; for example, if a project is sped up, it reduces overall road user, crash, and local business impacts.

6.3.2 Project Planning

Second, the tool can be used in the project planning stage to evaluate possible innovative scheduling opportunities. The tool can quantify the cost generated per day or per hour, and, as such, can inform decision makers of the economic benefits of reducing construction times. Each complex scenario, whether it includes time of day, duration of the project, traffic volumes, seasons, etc., can be compared with a dollar-per project amount. Likely project impact costs can be calculated for many scenarios before work is begun to determine the most efficient and cost-effective approach. This should be done early in the planning process, perhaps as part of the LCCA and prior to any design work, to effectively influence the overall budget and schedule. Road owners can further use the tool to create incentives/disincentives under contract using the per day or per vehicle impact costs to encourage contractors to reduce overall impacts.

6.3.3 Community Outreach

Finally, the tool can be used to illustrate to local business owners the potential loss—or lack of loss—in revenue they could receive during construction. As found through previous studies (Buddemeyer et al, 2008; Buffington & Wildenthal, 1997; Wildenthal & Buffington, 1996), actual revenue losses are not nearly as extreme as owner-perceived revenue losses. Explaining that results are assuming worst-case scenario situations could help ease business owners' nerves and lower potential conflict points. Furthermore, increasing communication between the road owner and community regarding project updates and timelines has been shown to increase positive public perception and relations (Buddemeyer et al, 2008).

CHAPTER 7: CONCLUSIONS

This study presents a comprehensive set of data-driven, nationally transferrable metrics that quantify the costs associated with asphalt and concrete pavement rehabilitation in terms of (a) road user costs, (b) crash mitigation costs, and (c) local business impact costs. These metrics are combined into a convenient Excel tool for users to input project variables and receive associated direct and indirect cost projections.

Specifically, costs are characterized in three ways: Road User Costs (RUCs) are defined as the total monetary and temporal costs experienced by both personal and freight vehicle road users when faced with delays caused by lane or total road closures due to rehabilitation work. Crash Mitigation Costs (CMCs) are defined as the cost associated with the most likely crash type to occur at a work zone. Local Business Impact Costs (LBICs) are defined as the economic impacts on local businesses from nearby pavement rehabilitation work zones caused by changes in customer spending and visitation behaviors.

Nationally representative data was collected for each Road User Cost category, including from the Highway Safety Information System (HSIS) and a unique national travel behavior survey conducted specifically for this study, and models to predict these costs for given roadway environments were estimated, using ordered probit regression models.

Overall, the results from the study indicate that impacts on road users, crashes and local businesses are governed not just by the project construction characteristics and the roadways on which the projects occur but the interactions with the drivers and vehicles on those roadways. As a result, when estimating these costs, it is imperative to simulate the traffic that travels through the resulting work zones, and the tool developed in this project does this.

Additionally, the tool incorporates the difference in costs generated for personal and freight vehicles. Travel for leisure versus freight deliveries and vehicle class greatly affect the impact cost.

Finally, applications of the Excel workbook highlight that small increases in travel delay have significant impacts on local businesses.

CHAPTER 8: SUGGESTIONS FOR FUTURE WORK

Over the course of this thesis, three future studies were identified and determined outside the scope of this work: determining the average time and cost per mile of pavement rehabilitation projects, determining the critical delay time signifying change in user behavior, and updating traffic flow factors. What follows are brief proposals for each study.

Early on, it became apparent that reporting realistic work zone durations and costs per mile would be beneficial to the overall accuracy of the final model. However, very little US-based research was found that quantified the temporal and monetary costs differences between asphalt cement (AC) and Portland cement concrete (PCC) rehabilitation roadway projects. What could be found regarding costs and benefits for each type was highly subjective. This was mainly due to the studies being conducted by lobbyist/activist groups for AC and PCC who would present information that sometimes contradicted each other. Additionally, while there are historical cost estimates available through state DOTs/road owners, no known national set metrics exist to our knowledge. Therefore, it is proposed that a study be done to determine the average expected dollar cost as well as expected duration of different pavement rehabilitation projects on a per mile basis.

As stated in section 5.2, there is an identifiable critical time between delay times of 5 and 20 minutes resulting in a change in respondent behavior. As the delay data used was categorical instead of continuous, the exact critical delay time could not be identified. Determining this point could have wide-reaching applications and would improve the Excel tool presented in chapter 6. Therefore, it is proposed that a study using a similar survey design, as presented in chapter 5, be conducted with random delay increases distributed to respondents.

In subsection 3.1.1, of this thesis, AADT conversion factors and the diversion equation were presented to the reader. It was noted that the AADT conversion factors were from a Georgia DOT study conducted in 1999 which, while still serviceable, could be outdated or inaccurate given the localization of the study area. As noted, traffic diversion factors are heavily location-dependent, preventing universal values from existing. Therefore, it is proposed a study be conducted to validate the AADT conversion factors as well as create a set of AADT conversion factors categorized by state (or other division), roadway type, and surrounding location. If possible, determining a set of localized traffic diversion factors from previous work zone studies would also be beneficial in assisting planners during the traffic control phase of projects.

REFERENCES

Agahi, N., Ahacic, K., & Parker, M. G. (2006). Continuity of leisure participation from middle age to old age. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *61*(6), S340-S346.

Agrawal, S., Song, D. Y., Peeta, S., & Benedyk, I. (2018). Driving Simulator Based Interactive Experiments: Understanding Driver Behavior, Cognition and Technology Uptake under Information and Communication Technologies (No. NEXTRANS Project No. 143PUY2. 1).

American Association of State Highway and Transportation Officials. (2010). *User and Non-User Benefit Analysis for Highways.* AASHTO, Washington, DC.

American Society of Civil Engineers and the Eno Center for Transportation. (2014). *Maximizing the Value of Investments Using Life Cycle Cost Analysis*. Washington, DC.

Asphalt Pavement Alliance (2011). Life-cycle cost analysis: A position paper. *Lanham, MD*.

Asphalt Pavement Alliance. (2016). *Life Cycle Cost Analysis Original*. Software.

Atchley, R. C. (1989). A continuity theory of normal aging. *The gerontologist*, *29*(2), 183-190.

ATCHLEY, R. (1993). Continuity theory and the evolution of activity in later adulthood. *Activity and Aging*, 5-16. Babashamsi, P., Yusoff, N. I. M., Ceylan, H., Nor, N. G. M., & Jenatabadi, H. S. (2016). Evaluation of pavement life cycle cost analysis: Review and analysis. *International Journal of Pavement Research and Technology*, *9*(4), 241-254.

Bai, Y. (2006). *Determining major causes of highway work zone accidents in Kansas*. University of Kansas Center for Research, Inc..

Bogers, E., Viti, F., & Hoogendoorn, S. (2005). Joint modeling of advanced travel information service, habit, and learning impacts on route choice by laboratory simulator experiments. *Transportation Research Record: Journal of the Transportation Research Board*, (1926), 189-197.

Bonneson, J., National Research Council (US), Transportation Research Board, Task Force on Development of the Highway Safety Manual, & Transportation Officials. Joint Task Force on the Highway Safety Manual. (2010). *Highway safety manual* (Vol. 1). AASHTO.

Borchardt, D. W., Pesti, G., Sun, D., & Ding, L. (2009). Capacity and road user cost analysis of selected freeway work zones in Texas. *Austin, TX. Texas Department of Transportation, Austin, TX*.

Buddemeyer, J., Young, R. K., & Vander Giessen, S. (2008). Highway Construction Related Business Impacts: Phase 3 Effort for the Town of Dubois (No. FHWA-WY-08/01F).

Buffington, J. L., & Wildenthal, M. T. (1997). Estimated Construction Period Impact of Widening State Highway 199 in Parker County, Texas (No. FHWA/TX-98/1260-2).

Bureau of Labor Statistics. (2017). Table B-3: Average Hourly and Weekly Earnings of All Employees on Private Nonfarm Payrolls by Industry Sector, Seasonally Adjusted. United States Department of Labor.

Calfee, J., & Winston, C. (1998). The value of automobile travel time: implications for congestion policy. *Journal of Public Economics*, 69(1), 83-102.

Carman, J. M. (1969). Some insights into reasonable grocery shopping strategies. *The Journal of Marketing*, 69-72.

Census Bureau, U. S. C. (2010). 2006-2010 American Community Survey 5-Year Estimates.

Census Bureau, U. S. C. (2015). “Community Facts: 2011-2015 American Community Survey 5-Year Estimates.” US Department of Commerce.

Census Bureau, U. S. C. (2016). “United States Population Growth by Region.” US Department of Commerce.

Church, J. D. (2016). Comparing the Consumer Price Index with the gross domestic product price index and gross domestic product implicit price deflator. *Monthly Lab. Rev.*, *139*, 1.

Cunningham, R. M. (1956). Brand loyalty-what, where, how much. *Harvard Business Review*, 34(1), 116-128.

Cunningham, R. M. (1961). Customer loyalty to store and brand. *Harvard Business Review*, 39(6), 127-137.

Daniels, G., Ellis, D. R., & Stockton, W. R. (1999). *Techniques for manually estimating road user costs associated with construction projects* (Vol. 3). Texas, USA: Texas Transportation Institute.

Debnath, A. K., Blackman, R., & Haworth, N. (2015). Common hazards and their mitigating measures in work zones: A qualitative study of worker perceptions. *Safety science*, *72*, 293-301.

Di, X., Liu, H. X., Zhu, S., & Levinson, D. M. (2017). Indifference bands for boundedly rational route switching. *Transportation, 44*(5), 1169-1194.

Duncan, C., Khattak, A., & Council, F. (1998). Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions. *Transportation Research Record: Journal of the Transportation Research Board*, (1635), 63-71.

Federal Highway Administration. (2017a). Facts and Statistics – Work Zone Safety. *Washington, DC: US Department of Transportation*.

Federal Highway Administration. (2017b). Highway Statistics 2016: Table HM-12. *Washington, DC: US Department of Transportation*.

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T. K. (2008). Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation, 35*(1), 37-54.

Gärling, T., & Axhausen, K. W. (2003). Introduction: Habitual travel choice. *Transportation, 30*(1), 1-11.

Gluck, J. S., Levinson, H. S., & Stover, V. G. (1999). *Impacts of access management techniques* (NCHRP. 420). Transportation Research Board.

Harwood, D. W., Council, F. M., Hauer, E., Hughes, W. E., & Vogt, A. (2000). *Prediction of the expected safety performance of rural two-lane highways* (No. FHWA-RD-99-207, MRI 4584-09, Technical Report). United States. Federal Highway Administration.

Institute of Transportation Engineers. (1999). *Transportation Planning Handbook*. 2nd Ed. Washington, DC.

Jiang, Y. (2001, January). Estimation of traffic delays and vehicle queues at freeway work zones. In *J. Transp. Res. Forum* (Vol. 40, No. 4, pp. 65-81).

Karim, A., & Adeli, H. (2003). Radial basis function neural network for work zone capacity and queue estimation*. Journal of Transportation Engineering*, 129(5), 494-503.

Khattak, A. J., Khattak, A. J., & Council, F. M. (2002). Effects of work zone presence on injury and non-injury crashes. *Accident Analysis & Prevention*, 34(1), 19-29.

Khattak, A., Kanafani, A., & Le Colletter, E. (1994). Stated and reported route diversion behavior: Implications on the benefits of ATIS.

Kockelman, K. M., & Kweon, Y. J. (2002). Driver injury severity: an application of ordered probit models. *Accident Analysis & Prevention, 34*(3), 313-321.

Lam, T. C., & Small, K. A. (2001). The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E: Logistics and Transportation Review*, 37(2-3), 231-251.

Li, Y., & Bai, Y. (2008). Development of crash-severity-index models for the measurement of work zone risk levels. *Accident Analysis & Prevention*, *40*(5), 1724-1731.

Mallela, J., & Sadavisam, S. (2011). *Work Zone Road User Costs: Concepts and Applications*. US Department of Transportation, Federal Highway Administration.

Memmot, J. L., & McFarland, W. F. (1988). Estimating User Costs of Asphalt and Concrete Pavement Rehabilitation. *Transportation Research Record: Journal of the Transportation Research Board*, (No. IS-107).

Meng, Q., Weng, J., & Qu, X. (2010). A probabilistic quantitative risk assessment model for the long-term work zone crashes. *Accident Analysis & Prevention*, *42*(6), 1866-1877.

National Highway Traffic Safety Administration. (2015). Traffic Safety Facts 2014 (DOT HS 812 261). *Washington, DC: US Department of Transportation*.

Outwater, M., Castleberry, S., Shiftan, Y., Ben-Akiva, M., Shuang Zhou, Y., & Kuppam, A. (2003). Attitudinal market segmentation approach to mode choice and ridership forecasting: Structural equation modeling. *Transportation Research Record: Journal of the Transportation Research Board*, (1854), 32-42.

Pinjari, A. R., & Bhat, C. (2006). Nonlinearity of response to level-of-service variables in travel mode choice models. *Transportation Research Record: Journal of the Transportation Research Board*, (1977), 67-74.

Pinjari, A. R., Pendyala, R. M., Bhat, C. R., & Waddell, P. A. (2011). Modeling the choice continuum: an integrated model of residential location, auto ownership, bicycle ownership, and commute tour mode choice decisions. *Transportation*, *38*(6), 933.

Rao, T. R. (1969). Consumer's purchase decision process: stochastic models. *Journal of Marketing Research*, 321-329.

Schultz, G. G., Braley, K. T., & Boschert, T. (2009). Relationship between access management and other physical roadway characteristics and safety. *Journal of transportation engineering*, *136*(2), 141-148.

Small, K. A. (1999). Valuation of travel-time savings and predictability in congested conditions for highway user-cost estimation (Vol. 431). Transportation Research Board.

Song, Z., Yin, Y., & Srinivasan, S. (2011). Modeling diversion propensity at work zones. In *ICCTP 2011: Towards Sustainable Transportation Systems* (pp. 3997-4012).

Tang, Y., & Chien, S. I. (2010). Optimization of Work Zone Schedule Considering Time-varying Traffic Diversion *Transportation Research Record: Journal of the Transportation Research Board*, (No. 10-0184).

Thorhauge, M., Haustein, S., & Cherchi, E. (2016). Accounting for the Theory of Planned Behaviour in departure time choice. *Transportation Research Part F: Traffic Psychology and Behaviour*, 38, 94-105.

Ullman, G. L. (1992). Natural diversion at temporary work zone lane closures on urban freeways in Texas. Interim Report (No. FHWA/TX-92/1108-6).

Ullman, G. L. (1996). Queuing and natural diversion at short-term freeway work zone lane closures. *Transportation Research Record: Journal of the Transportation Research Board*, (1529), 19-26.

Van Nostrand, C., Sivaraman, V., & Pinjari, A. R. (2013). Analysis of long-distance vacation travel demand in the United States: a multiple discrete–continuous choice framework. *Transportation*, *40*(1), 151-171.

Wildenthal, M., & Buffington, J. (1996). Estimated construction period impact of widening State Highway 21 in Caldwell, Texas. *Transportation Research Record: Journal of the Transportation Research Board*, (1559), 76-83.

Ye, L., Mokhtarian, P. L., & Circella, G. (2012). Commuter impacts and behavior changes during a temporary freeway closure: the 'Fix I-5'project in Sacramento, California. *Transportation Planning and Technology*, *35*(3), 341-371.

Yu, J. W., & Peeta, S. (2011). Experimental analysis of a hybrid route choice model to capture dynamic behavioral phenomena under advanced information systems. *KSCE Journal of Civil Engineering*, 15(1), 175-185.