JOURNAL of the TRANSPORTATION RESEARCH FORUM

Volume 54, Number 1 Spring 2015

Transportation Research Forum
NDSU Dept. 2880
PO Box 6050
Fargo, ND 58108-6050
www.trforum.org

Journal of the Transportation Research Forum

The Transportation Research Forum, founded in 1958, is an independent, nonprofit organization of transportation professionals who conduct, use, and benefit from research. Its purpose is to provide an impartial meeting ground for carriers, shippers, government officials, consultants, university researchers, suppliers, and others seeking exchange of information and ideas related to both passenger and freight transportation. More information on the Transportation Research Forum can be found on the Web at www.trforum.org.

Disclaimer:

The facts, opinions, and conclusions set forth in the articles contained herein are those of the authors and quotations should be so attributed. They do not necessarily represent the views and opinions of the Transportation Research Forum (TRF), nor can TRF assume any responsibility for the accuracy or validity of any of the information contained herein.

Memberships/Subscriptions:

Subscriptions and/or membership forms may be obtained from the following office or online.

ISSN 1046-1469

Published and Distributed by
Transportation Research Forum
NDSU Dept. 2880
P.O. Box 6050
Fargo, ND 58108-6050
P: (701) 231-7766 • F: (701) 231-1945

or apply online at www.trforum.org

Journal of the Transportation Research Forum
Volume 54, Number 1 • Spring 2015

Table of Contents

On the cover: Congestion on urban freeways during peak times of the day is a universal transportation problem. Shy Bassan investigates the traffic efficiency gained by restricting heavy truck traffic during peak hours in "Review, Experimental Evaluation and Policy Considerations of a Directional Time of Day Truck Restriction on Highways." He found that prohibiting trucks in all lanes during the 4-6 p.m. period improved average travel time, total travel time, and average traffic speed by 8%–12%.

A Message from the JTRF Co-General Editors

The Spring 2015 issue of *JTRF* contains the usual wide variety of contemporary transportation topics that is the distinguishing characteristic of *JTRF*. Topics in this issue include the following:

- Causes of Missouri fatal crashes of teenagers
- Equity of sustainable mileage-based user fees
- Airline code-sharing
- Horizontal cooperation in gas transportation networks
- Multi-vehicle crashes involving large trucks
- Directional time of day truck restrictions
- Converting stop-controlled intersections to roundabouts

In "Contributing Circumstances Impact on Missouri Teenage Driver Crash Fatalities," Jill Bernard and Donald Sweeney analyze circumstances that may contribute to Missouri teenage driver fatalities. The authors also produce information relevant for the enhancement of Missouri's graduated drivers licensing (GDL) programs. They compare the frequencies of contributing circumstances of fatal crashes among teenage and older drivers, and a multinomial logistic regression model is used to predict the probability of crash severity under different circumstances. Bernard and Sweeney found that driving too fast for conditions, speeding, inattention, and driving on the wrong side are major factors that increase the likelihood of a fatality occurring.

Mark Burris and co-authors examined equity changes from the imposition of a mileage-based user fee (MBUF) in "Equity Evaluation of Sustainable Mileage-Based User Fee Scenarios." The objective of the paper is to examine the equity impacts resulting from not only a change in how transportation funding is assessed and collected, but also how it is spent. Using the 2009 National Household Travel Survey the authors examined four scenarios. They found that a scenario where an MBUF is combined with a federal tax and includes a greater focus on maintenance spending was the most geographically equitable. The authors also found that considering funding disbursement when examining the effect of a shift to MBUF may change the equity of different scenarios compared with when funding disbursement is not considered.

In "Is the Decision to Code-Share a Route Different for Virtual and Traditional Code-Share Arrangements?" Yan Du and B. Starr McMullen analyze factors that determine whether alliance carriers choose to remain in or leave a code-share on a route is significantly different for virtual and traditional code-share routes. They found that factors affecting alliance firms' code-sharing decisions significantly differ for virtual versus traditional code-share agreements. Virtual code-sharing tends to take place in less dense markets and is not significantly affected by yields. This provides tentative support for the argument that virtual code-sharing provides a mechanism by which carriers practice price discrimination. The authors found that traditional code-sharing is more likely to occur in dense markets, and high yields increase the probability of such arrangements. They conclude that traditional code-sharing is used to achieve the networking economics and cost saving derived from dense markets and appears to be more effective as a way to introduce competition into a market.

Rafay Ishfaq, Mark Clark, and Uzma Raja present a coordination approach for the expansion of gas transportation networks in "Horizontal Cooperation in Network Expansion: An Empirical Evaluation of Gas Transportation Networks." The contribution of the study is to propose an arrangement for network expansion based on horizontal cooperation among competitors. That is, companies that would otherwise compete, cooperate to serve respective segments of the market

through mutual agreement. The authors conduct an empirical study of the natural gas market in the southeastern United States which shows that horizontal cooperation among pipeline companies allows for expanding gas transportation networks efficiently to serve new customers. The authors say the benefits of coordination are identified through key structural elements such as the number and location of additional pipeline links, lower infrastructure expansion costs, and demand segmentation for the pipelines.

In "Multi-Vehicle Crashes Involving Large Trucks: A Random Parameter Discrete Outcome Modeling Approach," Mouyid Islam analyzes the injury severities of multi-vehicle large truck crashes. To do this, he uses two random parameter discrete outcome models – random parameter ordered probit and mixed logit. The models were estimated to predict the likelihood of five injury severity outcomes – fatal, incapacitating, non-incapacitating, possible injury, and no-injury. The author found that distracted and sleepy driving, male occupants (drivers or passengers), drivers residing or working in Texas, and not using seat belts increased the risk of being seriously injured in a multi-vehicle collision with a large truck. He concluded that the level of injury severity is influenced by a number of complex interactions of human vehicular, road-environmental, and crash dynamics factors that vary across observations.

Shy Bassan examines a policy that investigates traffic efficiency gained by restricting heavy truck traffic in one direction during afternoon peak hours in "Review, Experimental Evaluation, and Policy Considerations of a Directional Time of Day Truck Restriction on Highways." The objective of the study is to estimate the benefit of restricting truck traffic in the traffic stream according to three traffic-flow parameters: average travel time, total travel time, and average traffic speed. He conducted an empirical study involving Highway 1 in Israel. He found that prohibiting trucks in all lanes in one direction during the period 4 pm–6 pm improved all three flow parameters by 8%–12%. The author found that segments of Highway 1 that had the steepest grades had the most improvement in the traffic stream parameters.

In "Safety and Economic Assessment of Converting Two-Way Stop Controlled Intersections to Roundabouts on High Speed Rural Highways," Shanshan Zhao, Aemal Khattak, and Eric Thompson investigate the economic and safety benefits of roundabouts. The authors investigate two research questions: "Are roundabouts on rural high speed highways safer than two-way stop-controlled (TWSC) intersections?" and "What economic benefits can be expected from the conversion of TWSC intersections to roundabouts in terms of safety improvement?" To answer these questions, crash records for several TWSC intersections that were later converted to roundabouts were obtained from the Kansas Department of Transportation. A before-after analysis using the Empirical Bayes (EB) method was utilized. The results showed that fatal, non-fatal, and property damage only crashes were reduced by 100%, 76.5% and 35.5%, respectively. The annual value from this reduction was between $1.0 and $1.6 million in 2014 dollars.

Michael W. Babcock
Co-General Editor

James Nolan
Co-General Editor

Contributing Circumstances Impact on Missouri Teenage Driver Crash Fatalities

by Jill M. Bernard and Donald C. Sweeney II

Missouri data from 2002-2011 are used to analyze the major circumstances that increase the risk of fatality in crashes involving teenage drivers, given a motor vehicle crash occurs. The frequencies of contributing circumstances among teenage and older drivers are compared and a multinomial logistic regression model is used to predict the probability of crash severity under different circumstances. For crashes involving teenage drivers, it is found that driving too fast for conditions, speeding, inattention, and driving on the wrong side are the most frequent circumstances cited in fatal crashes, and are major factors that increase the likelihood of a fatality occurring.

INTRODUCTION

Motor vehicle traffic crashes are the leading cause of death for United States teenagers (Miniño 2010), accounting for the loss of over 2,800 teen lives in 2012 alone (Insurance Institute for Highway Safety 2014). It has been found that teenagers often lack adequate driving skills and exhibit poor driving judgment (University of Michigan Transportation Research Institute 2002), and teenage drivers are more likely than older drivers to exhibit reckless and risky behavior: i.e., drive at excessive speeds, violate traffic signals, follow too closely, overtake other vehicles in a risky manner, allow too little time to merge, and fail to yield to pedestrians (Williams 2003). Accordingly, much research has examined the effect of specific factors on teenage driver fatalities and focused upon preventive measures to enhance teenage driver safety.

Graduated Drivers Licensing (GDL) programs have been shown to enhance teenage driver safety and significantly reduce the rate of teenage driver fatalities. Yet, it has been claimed that "reductions in fatal crashes were greatest in states that had enacted other restrictions on young drivers" (U.S. Department of Health and Human Services, National Institute of Health 2011). As a result, the purpose of this study is to analyze circumstances that may contribute to Missouri teenage driver fatalities and to produce information relevant for the enhancement of Missouri's GDL program. The analysis compares the frequency of contributing circumstances occurrences leading to fatal crashes of drivers 16 to 19 years old and older drivers, determines the probability of a fatal crash for teenage drivers given a contributing circumstance or combination of contributing circumstances, as well as explores the impact of contributing circumstances in combination with varying speed limits and environmental factors, (road surface, road alignment, road profile, road conditions, weather condition, light conditions) while controlling for the crash location (on or off the roadway) and number of occupants. The paper concludes with findings that will be useful for legislation and education to aid in diminishing crash injury severity for teenage drivers.

LITERATURE REVIEW

In order to protect U.S. teenage and other drivers, all 50 states and the District of Columbia have imposed GDL restrictions on drivers under the age of 21. GDL programs are designed to delay full licensure and phase in driving privileges (National Highway Traffic Safety Administration n.d.) with the intent to "encourage new drivers to acquire critical driving skills and experience in low-risk and monitored settings" (Dee et al. 2005). In a three-staged GDL program, new drivers begin

in an instructional, supervised practice phase, proceed to a provisional license that temporarily restricts unsupervised driving, and then graduate to an under 21 full driver's license (Williams 2003, Mayhew et al. 1998). Requirements for progressing through GDL's three stages (learner's permit, provisional licensure, and full licensure) vary across jurisdictions (Insurance Institute for Highway Safety, Highway Loss Data Institute 2011), but typically include adult supervision, restriction on nighttime driving, and limitations on transportation of young passengers (University of Michigan Transportation Research Institute 2002).

Many studies have been conducted to determine if these GDL policies are effective in reducing teenage crashes. Foss et al. (2001) assessed crash rates before and after North Carolina's GDL program implementation, and discovered that crash rates declined sharply among 16-year-old drivers. Likewise, Shope and Molnar (2004) evaluated the effectiveness of Michigan's GDL program by assessing the difference between motor-vehicle crash data for 16-year-old drivers pre-GDL and post-GDL. Results indicated that risk reduction for crash injury severity for all fatal and non-fatal injuries were substantial and impressive, and it was claimed that the "GDL remains promising." Fohr et al. (2005) considered the implementation of Wisconsin's GDL, and discovered that for 16- and 17-year-olds both general and injury crash rates declined. The authors claimed that the decline was the result not of safer driving of teens, but rather due to reduced exposure to the risk of collision. Rios et al. (2006) developed a generalized linear model to assess the impact of Georgia's Teenage and Adult Drivers Responsibility Act (TADRA) on the reduction of teenage driver fatalities. Findings indicated that speed-related teenage fatal crashes and alcohol-related teenage fatal crashes significantly decreased after the TADRA was enacted. Additionally, Hyde et al. (2005) assessed if crash rates of 16-year-old drivers decreased after implementation of Utah's GDL by examining overall crash rates, crash severity indicators, nighttime crashes, licensure status, seat belt usage, and citations. Using an interventional time series analysis, findings implied that the GDL program may have contributed to minimal reduction in teenage driver crashes, compared with other GDL evaluations. Ehsani et al. (2013) also used a time-series analysis to assess the impact of GDL on crash injury severity of 16-, 17- and 18-year-old drivers in Maryland, Florida, and Michigan. Results suggested that crash rates for drivers 16 and 17 years old declined in all three states following GDL implementation or revision, while crash rates for possible injury/property damage only for 18-year-old drivers decreased in Maryland, increased in Michigan, and did not significantly change in Florida following GDL implementation or revision. Other recent studies have focused on the impact of contributing circumstances on crash injury severity for young people. Amarasingha and Dissanayake (2013) developed a multinomial model to examine the impact of contributory factors on crash severity for young drivers involved in crashes in Kansas. Findings suggested that failure to give time/attention, failure to yield, driving too fast for conditions, falling asleep, following too closely, and distraction/inattention increased the crash risk for young drivers, and such findings can be useful in teen driving safety efforts. Similar to Amarasingha and Dissanayake (2013) and Ehsani et al. (2013), this study estimates the impact of contributing circumstances on crash injury severity for young drivers and considers the impact of these factors on the GDL policy. Yet, unlike the reviewed literature, this study concentrates specifically on the state of Missouri and explores possible scenarios to aid in enhancing Missouri teenage licensing policy.

Missouri Graduated Drivers Licensing Program

The Missouri GDL program was enacted as part of Senate Bill (SB) 19 passed in the 1999 legislative session, and put into effect January 1, 2001. The legislation requires that all first-time drivers between the ages of 15 and 18 years old complete a period of driving with a licensed driver followed by a period of restricted driving before graduating to an under 21 full driver's license (Missouri Department of Revenue 2014).

The 2001 Missouri GDL program implemented three significant policies: (1) a six month mandatory holding period of the learner permit, (2) prohibition of unsupervised driving from 1:00 a.m. to 5:00 a.m. during the intermediate license phase, and (3) the requirement of 20 hours of supervised driving instruction. Significant revisions to the GDL program were enacted in 2006 and 2007 to include: (1) restrictions on passengers in vehicles operated by drivers in the intermediate phase, whereby in the first six months no more than one passenger under the age of 19 and thereafter, no more than three passengers under the age of 19 are permitted, and (2) first-time drivers between the ages of 15 and 18 to require 40 hours of driving instruction, including a minimum of 10 hours of nighttime driving with a parent, legal guardian, grandparent, qualified driving instructor or certified trainer (Missouri Department of Revenue 2014). All current GDL requirements for Missouri teenage drivers may be found in Appendix A, and a comparison of Missouri's policy with the remaining states and Washington D.C. GDL policies is presented in Table 1.

DATA

The Missouri State Highway Patrol (MSHP) Traffic Division is the statewide repository for traffic crash reports. The MSHP collects and preserves crash report data to provide computerized records for research and analysis purposes. The Traffic Division codes and classifies the reports for entry in the Statewide Traffic Accident Records System (STARS) database, and is "responsible for maintaining the official count of motor vehicle crash fatalities for the State of Missouri" (Missouri

Table 1: Comparison of GDL Laws

	Lerner Stage			Intermediate Stage		Full License	
	Minimum Age (Years/Months)	Minimum Duration (Days or Months)	Required Supervised Driving Hours (Night Hours)	Minimum Age (Year/Months)	Nighttime Driving Restrictions	Passenger Restrictions	Minimum Age (Years/Months)
Restriction (# of states)[1]	14 (6) 14 / 6 (2) 14 / 9 (1) 15 (MO + 22) 15 / 6 (9) 15 / 9 (1) 16 (8 + D.C.)	None (1) 10 days (1) 4 mos. (1) 6 mos. (MO + 34 + D.C.) 180 days (1) 9 mos. (3) 12 mos. (8)	Some supervised driving (MO + 45 + D.C.) None (4)	14 + 180 days (1) 15 (2) 15 / 6 (2) 16 (MO + 33) 16 / 3 (1) 16 / 4 (1) 16 / 6 (8 + D.C.) 17 (1)	Some nighttime restrictions (MO + 48 + D.C.) None (1)	Some passenger restrictions (MO + 46 + D.C.) None (3)	16 (3) 16 / 6 (11) 16 / 9 (1) 17 (14) 17 / 6 (1) 18 (MO + 7 + D.C.) Varies (12)

[1]The information provided in parentheses indicates the total number of states (excluding Missouri) that adheres to the relevant policy and/or if Missouri (MO) or Washington DC (D.C.) adhere to the relevant policy.
Source: Governors Highway Safety Association (2014)

Traffic Records Committee 2002). Traffic, personal, and vehicle crash data from 2002-2011 were obtained from the STARS database. Approximately 2.3 million usable records of Missouri drivers in a crash were analyzed to determine if a significant relationship exists between the contributing circumstances indicated below and teenage driver fatalities.

After a crash occurs, at least one, but no more than five, of the following contributing circumstances at the driver level are identified per vehicle as determined by the crash investigator (Missouri Traffic Records Committee 2002).

1. Vehicle Defects
2. Traffic Control Inoperable/Missing
3. Improperly Stopped on Roadway
4. Speed – Exceeded Limit
5. Too Fast for Conditions
6. Improper Passing
7. Violation Signal /Sign
8. Wrong Side (not passing)
9. Following Too Close
10. Improper Signal
11. Improper Backing
12. Improper Turn
13. Improper Lane Usage / Change
14. Wrong Way (One-Way)
15. Improper Start From Park
16. Improperly Parked
17. Failed to Yield
18. Alcohol
19. Drugs
20. Physical Impairment
21. Inattention
22. None

METHODOLOGY

Cross-Tabulation

Cross-tabulation is employed to examine the frequency of fatal crashes in order to determine if contributing circumstances are more or less prevalent among teenage drivers. Table 2 below illustrates that driving too fast for conditions (25.9%), speeding (20.6%), inattention (18.3%), driving on the wrong side of the road (14.9%), alcohol (14.1%), and improper lane usage (13.6%) are the most frequent contributory circumstances cited in fatal crashes involving teenage drivers. Additionally, Table 2 presents chi-square tests to determine if significant differences exist between the frequency of contributing circumstances for 16- to 19-year-old drivers and older drivers, given a fatal crash occurs. Results from the chi-square tests indicate that, between the two age groups, the contributing circumstances of speeding, driving too fast for conditions, improper passing, driving on the wrong side of the road, alcohol, physical impairment, and inattention are significantly different at the 0.05 level. All significantly different circumstances are more prevalent for teenage drivers than for older drivers, with the exceptions of alcohol intoxication and physical impairment. Furthermore, the significantly lower prevalence of no contributing circumstance (i.e., none) in the 16- to 19-year-old age group suggests that teenagers are more likely to be a contributory driver, given a fatal crash occurs. As Table 2 indicates, 80.6% of teenage drivers involved in a fatal crash contributed to the crash (1-[260/1,338]), while only 63.6% of other drivers did (1-[3,688/10,135])!

Table 2: Frequency and Chi-Square Tests for Contributing Circumstances Leading to Fatalities in Years 2002-2011 for Drivers Aged 16 to 19 and Older Drivers

	Drivers Age		Chi-Square	
Contributing Circumstances	16-19	Other	Value	Sig.
Vehicle Defects	12	114	0.565	0.452
Speeding	275	1,077	112.034	0.000
Too Fast for Conditions	346	1,726	62.267	0.000
Improper Passing	36	181	5.213	0.022
Violation Signal /Sign	55	326	2.943	0.086
Wrong Side	199	954	38.979	0.000
Following Too Close	19	134	0.086	0.769
Improper Turn	10	79	0.160	0.900
Improper Lane Usage/Change	182	1,200	3.465	0.063
Failed to Yield	115	800	0.792	0.373
Alcohol	188	1,742	8.313	0.004
Drugs	37	263	0.135	0.714
Physical Impairment	28	373	8.833	0.003
Inattention	245	1,414	18.159	0.000
All Other Circumstances[1]	11	121	1.436	0.231
None	260	3,688	150.577	0.000
Total Number of Cases[2]	1,338	10,135		

[1] All Other Circumstances include Traffic Control Inoperable/Missing, Improperly Stopped on Roadway, Improper Signal, Improper Backing, Improper Start from Park, Improperly Parked, and Wrong Way.
[2] Total number of cases does not equal the sum of the frequency of contributing circumstances, since more than one circumstance may be present in a given crash.

Due to their impact and significance, factors that lead to driver inattention are further differentiated as: Cell Phone; Stereo/Audio/Video Equipment; Computer Equipment/GPS/Electronic Game/etc.; Passenger; Tobacco Use; Eating/Drinking; Reading; Grooming; Other; and Unknown. As depicted in Table 3, cell phone use and passengers in the vehicle are the two largest identified specific causes of inattention for drivers aged 16 to 19. For the 16- to 19-year-old age group, inattention caused by cell phone use not only has the highest relative percentage relating to teenage fatalities (with the exception of the combined "Other" category), but also a higher percentage when compared with older drivers.

Table 3: Causes of Inattention Relating to Fatalities from 2002-2011

	Frequency		
	Driver Age		
Cause of Inattention	16-19	Other	Total
Cell Phone	23	57	80
Stereo/Audio/Video Equipment	5	14	19
Computer/GPS/Electronic Game/etc.	0	2	2
Passenger	13	37	50
Tobacco Use	0	6	6
Eating/Drinking	0	12	12
Reading	0	3	3
Grooming	0	1	1
Other[1]	190	1,197	1,387
Total[2]	231	1,329	1,560

[1] Potential causes include external distractions, adjusting vehicle controls, adjusting safety devices, hands-free communication devices, etc.
[2] Unknown factors leading to inattention are not included in total.

Multinomial Logistic Regression

Focusing on drivers who contributed to a crash, a multinomial logistic regression is employed to estimate the probability that when specific combinations of contributing circumstances are present the crash severity is either fatal (1), personal injury - disabling major (2), personal injury - evident (3), personal injury - probable (4), or property damage only (5). Many studies have chosen the multinomial logit approach to control for possible systematic differential under-reporting when assessing crash injury severity (e.g., Shankar and Mannering 1996; Carson and Mannering 2001; Ulfarsson and Mannering 2004; Khorashadi et al. 2005; Islam and Mannering 2006; Kim et al. 2007; Malyshkina and Mannering 2008; Savolainen and Ghosh 2008; Schneider et al. 2009; Malyshkina and Mannering 2010; Rifatt et al. 2011; Schneider and Salovainen 2011; Yasmin and Eluru 2013; Ye and Lord 2014).

Since not all crashes are reported, other crash prediction models, such as ordered logit and probit models, can lead to biased parameter estimates (Ye and Lord 2014). Multinomial logit models do not consider the natural ordering of outcomes and therefore might be considered less parsimonious than ordered models; however, given a systematically under-reported outcome, a multinomial logit model offers greater explanatory power due to the additional exogenous effects that may be explored (Eluru 2013).

The multinomial logit model, where β_i is a vector of estimable parameters and X_{in} is a vector of observable variables that may impact the probability of crash severity outcome i for observation n (Savolainen et al. 2011) is presented in equation (1).

$$(1)\quad P_n(i) = \frac{\mathrm{EXP}[\beta_i^T \bullet \mathrm{X}_{in}]}{\sum_i \mathrm{EXP}\,[\beta_i^T \bullet \mathrm{X}_{in}]}$$

Savelonien et al. (2011) and Mannering and Bhat (2014) completed extensive reviews of the literature where multinomial logit methodologies were used to analyze crash injury severity. From a review of the identified studies, numerous variables are suggested to impact crash injury severity. These variables include driver's age (Schneider et al. 2009; Rifatt et al. 2011; Yasmin and Eluru 2013), passenger presence/number of passengers (Khorashadi et al. 2005; Islam and Mannering

2006; Savolainen and Ghosh 2008; Schneider et al. 2009), speed limit (Islam and Mannering 2006; Savolainen and Ghosh 2008; Schneider et al. 2009; Malyshkina and Mannering 2010; Yasmin and Eluru 2013), crash location (Savolainen and Ghosh 2008; Schneider et al. 2009), lighting conditions (Savolainen and Ghosh 2008; Rifatt et al. 2011; Yasmin and Eluru 2013), road conditions, surface and profile (Khorashadi et al. 2005; Kim et al. 2007; Malyshkina and Mannering 2008; Schneider et al. 2009), and weather conditions (Kim et al. 2007; Schneider and Salovainen 2011). As a result, these variables, in conjunction with contributory circumstances, have been included in the multinomial model since each may contribute to different crash severity outcomes.

The maximum likelihood ratio tests, parameter estimates and equation specific significance tests of the multinomial model with the baseline category of a property damage only severity outcome are presented in Table 4. The overall goodness of fit test with 1,165,745 observations yields a $\chi 2$ = 140,516.445 with p-value equal to 0.000).

As illustrated in the top panel of Table 4, the likelihood ratio tests indicate that all variables are significant in the model at the 0.000 significance level. The coefficients in the lower panel of Table 4, suggest the magnitude and directional impact of each factor on the level of injury severity (i.e., a term with a positive coefficient in the model will increase the probability of the outcome and a term with a negative coefficient in the model will decrease the probability of the outcome). Additionally, the Fatality column in the lower panel of Table 4 suggests that the presence of speeding, driving too fast for conditions, violating a stop sign or signal, driving on the wrong side of the road, driving while under the influence of alcohol or drugs, and driving while physically impaired are the contributing circumstances that have the greatest ceteris paribus increase on the probability of a fatal outcome, given a crash occurs. In addition, environmental factors of foggy/misty weather conditions and dark, unlit conditions also increase the probability of a fatal outcome. In contrast, wet, snowy or icy road conditions are suggested to decrease the likelihood of a fatal outcome, while rainy and snowy weather conditions have little relative impact. Finally, it is found that as the speed limit increases, the likelihood of a fatal outcome, given a crash occurs, also increases.

The model illustrates that the presence of certain drivers' contributions to a crash can dramatically change the probability of a fatal outcome when a motor vehicle crash occurs. Drawing upon the factors found to be more prevalent in the teenage age group (Table 2), the parameter estimates presented in Table 4 are employed to estimate probabilities of different crash severity outcomes under various scenarios. Table 5 presents the probability of each crash severity outcome for 16 to 19-year-old drivers involved in a crash composed of selected contributing circumstances and environmental factors.

- Base Scenario: A teenage driver who does not contribute to the crash driving during favorable conditions (straight, level, dry concrete road with clear weather conditions during daylight, and crash occurs on the roadway) in a 15 mph or 20 mph speed zone with one occupant (the driver) present in the vehicle.
- Scenario 1: An inattentive teenage driver driving on the wrong side of the road (exhibiting no other contributing behaviors) in a 55 mph or 60 mph speed zone with one occupant present during favorable conditions.
- Scenario 2: A speeding teenage driver driving in a 55 mph or 60 mph speed zone with one occupant present during favorable conditions.
- Scenario 3: A speeding teenage driver driving in a 65 mph or 70 mph speed zone improperly passing with one occupant present during favorable conditions.
- Scenario 4: A teenage driver driving too fast for unfavorable conditions (curvy/hilly dirt road, dark lighting conditions, and foggy/misting weather conditions) in a 55 mph or 60 mph speed zone with one occupant present and the crash occurs off the roadway.
- Scenario 5: A teenage driver speeding during unfavorable conditions (curvy/hilly dirt road, dark lighting conditions, and foggy/misting weather conditions) in a 55 mph or 60 mph speed zone with one occupant present and the crash occurs off the roadway.

Table 4: Multinomial Logistics Estimation Results of Probability of Crash Severity

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	**-2 Log Likelihood of Reduced Model**	**Chi-Square**	**df**	**Sig.**
Intercept	638,905.2	-	0	
Age Group	639,289.3	384.151	4	0.000
Vehicle Defects	638,968.4	63.189	4	0.000
Speeding	646,778.8	7,873.601	4	0.000
Too Fast for Conditions	642,896.9	3,991.735	4	0.000
Improper Passing	639,195.4	290.267	4	0.000
Violation Stop Sign / Signal	645,558.0	6,652.798	4	0.000
Wrong Side	642,214.4	3,309.268	4	0.000
Following Too Close	642,052.1	3,146.961	4	0.000
Improper Turn	639,055.4	150.209	4	0.000
Improper Lane Usage	639,581.6	676.443	4	0.000
Failed to Yield	644,036.9	5,131.696	4	0.000
Drinking	645,604.9	6,699.689	4	0.000
Drugs	639,456.4	551.199	4	0.000
Physical Impairment	644,158.6	5,253.417	4	0.000
Inattention	639,430.7	525.500	4	0.000
All Other Circumstances1	641,962.6	3,057.390	4	0.000
Number of Occupants	640,440.4	1,535.179	4	0.000
Road Surface	640,179.7	1,274.535	24	0.000
Road Alignment	639,369.4	464.260	8	0.000
Road Profile	640,870.4	1,965.238	12	0.000
Weather Conditions	639,258.8	353.643	28	0.000
Light Conditions	639,671.0	765.864	16	0.000
Road Conditions	641,483.6	2,578.407	16	0.000
Crash On/Off Roadway	643,919.3	5,014.125	4	0.000
Speed Limit	666,963.2	28,058.053	24	0.000

[1] All Other Circumstances include Traffic Control Inoperable/Missing, Improperly Stopped on Roadway, Improper Signal, Improper Backing, Improper Start from Park, Improperly Parked, and Wrong Way.

Factor	**Fatality**	**Sig.**	**Major Injury**	**Sig.**	**Evident Injury**	**Sig.**	**Probable Injury**	**Sig.**
Intercept	-7.569	0.000	-4.548	0.000	-2.759	0.000	-2.795	0.000
Driver's Age								
Age Group 16-19	-0.459	0.000	-0.070	0.000	0.059	0.000	-0.062	0.000
Driver Contributing Circumstance								
Vehicle Defects	-0.581	0.000	-0.049	0.115	0.024	0.210	-0.069	0.000
Speeding	2.433	0.000	1.331	0.000	1.021	0.000	0.548	0.000
Too Fast for Conditions	0.522	0.000	0.672	0.000	0.479	0.000	0.320	0.000

Table 4 continued

Factor	Fatality	Sig.	Major Injury	Sig.	Evident Injury	Sig.	Probable Injury	Sig.
Improper Passing	0.255	0.001	0.162	0.000	-0.203	0.000	-0.383	0.000
Violation Stop Sign / Signal	1.025	0.000	1.076	0.000	0.915	0.000	0.632	0.000
Wrong Side	1.604	0.000	0.989	0.000	0.583	0.000	0.063	0.008
Following Too Close	-1.782	0.000	-0.587	0.000	-0.300	0.000	0.230	0.000
Improper Turn	-0.647	0.000	-0.073	0.021	-0.054	0.002	-0.174	0.000
Improper Lane Usage	0.320	0.000	0.041	0.011	-0.029	0.008	-0.279	0.000
Failed to Yield	0.464	0.000	0.705	0.000	0.575	0.000	0.255	0.000
Alcohol	1.160	0.000	1.028	0.000	0.757	0.000	0.056	0.001
Drugs	0.973	0.000	0.636	0.000	0.425	0.000	0.480	0.000
Physical Impairment	1.035	0.000	1.262	0.000	1.006	0.000	0.873	0.000
Inattention	-0.052	0.099	0.122	0.000	0.107	0.000	0.147	0.000
All Other Circumstances	-0.315	0.001	-0.589	0.000	-0.855	0.000	-0.710	0.000
Environmental Factors								
Number of Occupants	0.087	0.000	0.079	0.000	0.063	0.000	0.052	0.000
Road Surface Unknown	-0.752	0.007	-0.187	0.017	-0.052	0.168	-0.103	0.003
Road Surface Asphalt	0.294	0.000	0.304	0.000	0.160	0.000	0.101	0.000
Road Surface Brick	-0.296	0.768	0.086	0.737	-0.516	0.001	0.011	0.918
Road Surface Gravel	0.025	0.730	0.248	0.000	0.214	0.000	-0.133	0.000
Road Surface Dirt or Sand	0.850	0.001	0.771	0.000	0.456	0.000	0.011	0.922
Road Surface Multi Surface	0.013	0.892	-0.016	0.701	-0.063	0.011	-0.058	0.016
Road Surface Concrete	0		0		0		0	
Road Alignment Unknown	-0.562	0.106	-0.073	0.480	-0.421	0.000	-0.361	0.000
Road Alignment Curve	0.263	0.000	0.184	0.000	0.050	0.000	-0.042	0.000
Road Alignment Straight	0		0		0		0	
Road Profile Unknown	-0.512	0.021	-0.572	0.000	-0.076	0.021	-0.125	0.000
Road Profile Hill/Grade	0.638	0.000	0.332	0.000	0.123	0.000	0.049	0.000
Road Profile Crest	0.478	0.000	0.339	0.000	0.257	0.000	0.056	0.003
Road Profile Level	0		0		0		0	
Weather Conditions Cloudy	0.099	0.001	0.000	0.968	-0.032	0.000	0.053	0.000
Weather Conditions Rain	-0.013	0.859	-0.199	0.000	-0.084	0.000	0.006	0.669
Weather Conditions Snow	-0.265	0.040	-0.291	0.000	-0.159	0.000	-0.067	0.011
Weather Conditions Sleet	-0.502	0.056	-0.095	0.248	-0.239	0.000	-0.041	0.433
Weather Conditions Freezing	0.063	0.703	0.014	0.829	-0.034	0.400	-0.006	0.879
Weather Conditions Fog/Mist	0.319	0.007	-0.083	0.160	0.064	0.081	0.033	0.408
Weather Conditions Indeterminate	0.453	0.030	-0.231	0.018	-0.300	0.000	-0.359	0.000
Weather Conditions Clear	0		0		0		0	
Light Conditions Indeterminate	-0.013	0.926	-0.181	0.001	0.041	0.142	-0.030	0.252
Light Conditions Dark - Streetlights On	0.104	0.013	-0.143	0.000	0.074	0.000	0.058	0.000
Light Conditions Dark - Streetlights Off	0.007	0.970	-0.150	0.045	0.050	0.223	-0.068	0.121

Table 4 continued

Factor	Fatality	Sig.	Major Injury	Sig.	Evident Injury	Sig.	Probable Injury	Sig.
Light Conditions Dark - No Streetlights	0.512	0.000	0.191	0.000	0.147	0.000	0.013	0.292
Light Conditions Daylight	0		0		0		0	
Road Conditions Other/ Unknown	-0.447	0.003	-0.352	0.000	-0.188	0.000	-0.010	0.756
Road Conditions Wet	-0.696	0.000	-0.493	0.000	-0.262	0.000	-0.075	0.000
Road Conditions Snow	-1.330	0.000	-1.040	0.000	-0.759	0.000	-0.346	0.000
Road Conditions Ice	-1.250	0.000	-0.937	0.000	-0.532	0.000	-0.190	0.000
Road Conditions Dry	0		0		0		0	
Crash On Roadway	-0.125	0.000	-0.386	0.000	-0.435	0.000	0.294	0.000
Crash Off Roadway	0		0				0	
Speed Limit 15-20 mph	-0.142	0.524	-0.242	0.000	-0.074	0.013	-0.136	0.000
Speed Limit 25-30 mph	0.436	0.008	0.240	0.000	0.323	0.000	0.256	0.000
Speed Limit 35-40 mph	1.238	0.000	0.781	0.000	0.716	0.000	0.599	0.000
Speed Limit 45-50 mph	1.909	0.000	1.244	0.000	0.883	0.000	0.546	0.000
Speed Limit 55-60 mph	2.731	0.000	1.841	0.000	1.168	0.000	0.690	0.000
Speed Limit 65-70 mph	2.875	0.000	1.742	0.000	0.917	0.000	0.390	0.000
Speed Limit Unknown	0		0		0		0	

Table 5: Probability of Crash Severity for 16- to 19-Year-Olds under Selected Scenarios

		Scenario				
Crash Severity	**Base**	**1**	**2**	**3**	**4**	**5**
P(Fatal)	0.0002	0.0137	0.0286	0.0362	0.0452	0.1807
P(Injury Disabling)	0.0051	0.0838	0.0902	0.0897	0.1977	0.2258
P(Injury Evident)	0.0384	0.1791	0.2152	0.1839	0.3198	0.3250
P(Injury Probable)	0.0633	0.1204	0.1457	0.1186	0.0658	0.0489
P(Property Damage)	0.8930	0.6030	0.5204	0.5716	0.3715	0.2196

The probabilities in Table 5 are computed employing equation (1) by first summing the product of the estimated coefficients for each severity outcome (the baseline category is normalized to sum to zero) and the values of the associated factors for each scenario, then computing the exponential of each of the five severity outcome summed products, and finally dividing each exponential by the sum of the five exponentials. For example, considering the base scenario, when a teenage driver is involved in a crash in a 15 mph or 20 mph speed limit zone, but does not contribute to the crash in any way and is driving under favorable conditions (straight, level, dry concrete road with clear weather conditions during daylight, and the crash occurs on the roadway), the probability of a fatal outcome is only 0.0002.

This probability is calculated by first computing the summed product of the scenario factors (e.g., teenager driving in a 15-20 mph zone) and associated estimated coefficients for each severity outcome. In the base case, the summed products of the outcome intercept + Age Group 16-19 outcome coefficient*1 + Number of Occupants outcome coefficient*1 + Crash on Roadway outcome coefficient*1 + Speed Limit 15-20 mph outcome coefficient*1 for each level of injury severity relative to the baseline of property damage only are:

Fatal = -7.569 + -0.459 + 0.087 + -0.125 + -0.142 = -8.208;
Injury Disabling = -4.548 + -0.07 + 0.079 + -0.386 + -0.242 = -5.167;
Injury Evident = -2.759 + 0.059 + 0.063 + -0.435 + -0.074 = -3.146;
Injury Probable = -2.795 + -0.062 + 0.052 + 0.294 + -0.136 = -2.647; and
Property Damage Only = 0.

The probability of each level of severity is then found by applying equation (1) as follows:

$$P(\text{Fatal}) = \frac{e^{-8.208}}{1+e^{-8.208}+e^{-5.167}+e^{-3.146}+e^{-2.647}} = 0.0002;$$

$$P(\text{Injury Disabling}) = \frac{e^{-5.167}}{1+e^{-8.208}+e^{-5.167}+e^{-3.146}+e^{-2.647}} = 0.0051;$$

$$P(\text{Injury Evident}) = \frac{e^{-3.146}}{1+e^{-8.208}+e^{-5.167}+e^{-3.146}+e^{-2.647}} = 0.0384;$$

$$P(\text{Injury Probable}) = \frac{e^{-2.647}}{1+e^{-8.208}+e^{-5.167}+e^{-3.146}+e^{-2.647}} = 0.0633; \text{ and}$$

$$P(\text{Property Damage Only}) = \frac{1}{1+e^{-8.208}+e^{-5.167}+e^{-3.146}+e^{-2.647}} = 0.8930.$$

As expected, when adding contributory circumstances and/or unfavorable conditions, the probability of a fatal outcome dramatically increases. In Scenario 1, when a teenage driver is involved in a crash resulting from inattentive behaviors that are accompanied by driving on the wrong side of the road (e.g., swerving, which has been found to commonly accompany texting and driving [Drews et al. 2009]) during favorable conditions with a single occupant and assuming zero values for all other variables, the probability of a fatal outcome rises to 0.0137.

Additionally, when considering teenagers involved in a crash where speeding in a speed limit zone of 55 or 60 mph occurred during favorable conditions, with a single occupant and assuming zero values for other variables as in Scenario 2, the probability that a fatal outcome will result in a crash increases further to 0.0286. When adding improper passing with speeding (both of which have been linked to head-on collisions (Gårder 2006), and increasing the speed limit zone to 65 mph or 75 mph, (Scenario 3), the probability that a teenage driver will be involved in a fatal crash (given a crash occurs) increases to 0.0362.

Lastly, when a teenage driver involved crash resulting from driving too fast in relatively poor conditions (curvy/hilly dirt road, dark lighting conditions, and foggy/misting weather conditions) in a speed limit zone of 55 mph or 60 mph, with a single occupant and the crash occurs off the roadway, assuming zero values for all other variables (Scenario 4), the probability of a fatality increases to 0.0452. However, when speeding rather than driving too fast for conditions (Scenario 5), while other factors remain unchanged, the likelihood of a fatal outcome drastically increases to 0.1807.

CONCLUSIONS

Prior national studies have found that GDL programs can significantly decrease the fatal crash rate of teenage drivers when additional restrictions are present (National Highway Traffic Safety Administration n.d.). Therefore, given the combination of prevalence among teenage drivers to be involved in crashes and the large impact on fatalities, legislation and education that further discourages the contributing circumstances of inattention and accompanying behaviors, speeding,

improper passing, driving too fast for conditions, and driving under the influence of alcohol and drugs should be considered for GDL policy to better protect and prepare Missouri teenage drivers.

Speeding, Driving Too Fast for Conditions, and Improper Passing

The current GDL requirements for Missouri teenage drivers, as detailed in Appendix A, include that during the instruction and intermediate phases, the driver may not have any traffic convictions in the last six months, and to graduate to an under-21 full driver's license the driver may not have any traffic convictions in the last 12 months. However, the consideration of a more stringent requirement for speed related traffic convictions could improve the efficacy of GDL policy. For example, if a conviction occurs, increasing the time required between the conviction and graduation from a GDL phase would increase the length of restricted driving time, allow inexperienced drivers additional time to gain experience in a controlled environment, and further encourage compliance with driving laws. Additionally, better preparation of properly obeying speed limits, recognizing unfavorable conditions that require speed reduction, and proper passing techniques should be considered. Since drivers who participate in the GDL program most likely lack experience, increased education on identified problem areas could encourage all teenagers to improve their driving behaviors.

Inattention and Accompanying Behaviors

Missouri Revised Statute Section 304.820 makes it illegal for 21-year-old and under drivers to text while driving (Joint Committee on Legislative Research 2012). In 2014, six additional distracted driver bills were brought before the Missouri Legislature. Contents of the bills include prohibition of handheld wireless communications devices by all drivers (House Bill 1106 and Senate Bill 840), addition of points against a driver's license for texting while driving, prohibiting the wearing of a head-mounted display while operating vehicles and increment of penalties for distracted driving law (House Bill 1123), prohibition of texting and driving by all drivers unless hands-free technology is used (House Bill 1256), and prohibition of text messaging by all drivers (House Bill 1282 and House Bill 1316) (Able 2014). The results of this study support the goals of these bills, and further indicate that the inclusion of additional cell-phone restrictions should be considered for improving the impact of the GDL program.

Intoxication

In order to graduate to an under-21 full driver's license, the intermediate driver may not have had any alcohol related offenses within the last 12 months. However, the consideration of more stringent requirements for alcohol and drug related convictions seem likely to increase the effectiveness of the existing GDL policy. Not only would harsher requirements reduce the number of full-licensed teenage drivers that exhibit poor driving judgment, but the increased delay of full driving privileges could also encourage teenagers who have not been convicted of such charges to better consider their behaviors before driving while intoxicated. Likewise, since older drivers are more likely to be involved in a fatal crash when alcohol is a contributing factor, given a crash occurs, harsher policies should also be considered for this population to increase overall traffic safety.

LIMITATIONS/FUTURE RESEARCH

It is important to note that this study assumes all drivers aged 16 to 19 years old have a GDL license with no special exemptions; however, some drivers may be permitted hours-related exemptions for employment or religious reasons. It is also important to recognize that the presence of the contributing circumstances are based on the investigator's judgment; therefore, while training

attempts to minimize variation among investigators, systematic discrepancies among investigator's judgment may occur.

The analysis of the data inferred that the group of Missouri driver's aged 20 to 24 years old have a large number of fatalities resulting from not only contributing circumstances, but also road types and surfaces, road conditions, and weather conditions. Future research may choose to focus on the factors leading to fatal crashes in this age group in order to provide information pertinent to future GDL revisions (i.e., extending GDL restrictions past 19 years old).

Future research may focus on changes in influence of contributing circumstances when temporary GDL restrictions are in place (i.e., restricted night driving) versus when GDL restrictions are lifted. The comparison of all drivers in the GDL program to all drivers not in the GDL program (independent of age) would also provide a better understanding of the experiential learning and restrictions being employed.

References

Able, Glen. "Missouri: Cell Phone Laws, Legislation." May 21, 2014. http://handsfreeinfo.com/missouri-cell-phone-laws-legislation (accessed May 29, 2014).

Amarasingha, Niranga and Sunanda Dissanayake. "Modeling Injury Severity of Young Drivers Using Highway Crash Data from Kansas." *Journal of the Transportation Research Forum* 52(1), (2013): 5-22.

Carson, Jodi and Fred Mannering. "The Effect of Ice Warning Signs on Ice-Accident Frequencies and Severities." *Accident Analysis & Prevention* 33(1), (2001): 99-109.

Drews, Frank A., Hina Yazdani, Celeste N. Godfrey, Joel M. Cooper, and David L. Strayer. "Text Messaging During Simulated Driving." *Human Factors: The Journal of the Human Factors and Ergonomics Society* (2009): 762-770.

Dee, Thomas S., David C. Grabowski, and Michael A. Morrisey. "Graduated Driver Licensing and Teen Traffic Fatalities." *Journal of Health Economics* 24(3), (2005): 571-589.

Ehsani, Johnathon P., C. Raymond Bingham, and Jean T. Shope. "Graduated Driver Licensing for New Drivers: Effects of Three States′ Policies on Crash Rates Among Teenagers." *American Journal of Preventive Medicine* 45(1), (2013): 9-18.

Eluru, Naveen. "Evaluating Alternate Discrete Choice Frameworks for Modeling Ordinal Discrete Variables." *Accident Analysis & Prevention* 55, (2013): 1-11.

Fohr, Susan Anderson, Peter M. Layde, and Clare E. Guse. "Graduated Driver Licensing in Wisconsin: Does it Create Safer Drivers?" *Wisconsin Medical Journal* 104(7), (2005): 31-36.

Foss, Robert D., John R. Feaganes, and Eric A. Rodgman. "Initial Effects of Graduated Driver Licensing on 16-year-old Driver Crashes in North Carolina." *Jama* 286(13), (2001): 1588-1592.

Gårder, Per. "Segment Characteristics and Severity of Head-On Crashes on Two-Lane Rural Highways in Maine." *Accident Analysis & Prevention* 38(4), (2006): 652-661.

Governors Highway Safety Association. "Graduated Drivers Licensing (GDL) Laws." *Governors Highway Safety Association*, 2014. http://www.ghsa.org/html/stateinfo/laws/license_laws.html (accessed August 2014).

Hyde, Lisa K., Lawrence J. Cook, Stacey Knight, and Lenora M. Olson. "Graduated Driver Licensing in Utah: Is it Effective?" *Annals of Emergency Medicine* 45(2), (2005): 147-154.

Insurance Institute for Highway Safety, Highway Loss Data Institute. "Young Driver Licensing Systems in the U.S." *Highway Safety Research & Communications*, 2011. http://www.iihs.org/laws/graduatedLicenseIntro.aspx (accessed November 2011).

Insurance Institute for Highway Safety, Highway Loss Data Institute. "Teenagers." *Highway Safety Research & Communications*, 2014. http://www.iihs.org/iihs/topics/t/teenagers/fatalityfacts/teenagers (accessed May 2014).

Islam, Samantha and Fred Mannering. "Driver Aging and Its Effect on Male and Female Single-Vehicle Accident Injuries: Some Additional Evidence." *Journal of Safety Research* 37(3), (2006): 267-276.

Joint Committee on Legislative Research. "Missouri Revised Statutes, Chapter 304, Traffic Regulations, Section 304.820 ." *Missouri Revised Statutes*, 2012.

Kim, Joon-Ki, Sungyop Kim, Gudmundur F. Ulfarsson, and Luis A. Porrello. "Bicyclist Injury Severities in Bicycle-Motor Vehicle Accidents." *Accident Analysis & Prevention* 39(2), (2007): 238-251.

Khorashadi, Ahmad, Debbie Niemeier, Venky Shankar, and Fred Mannering. "Differences in Rural and Urban Driver-Injury Severities in Accidents Involving Large-Trucks: An Exploratory Analysis." *Accident Analysis & Prevention* 37(5), (2005): 910-921.

Malyshkina, Nataliya V. and Fred Mannering. "Effect of Increases in Speed Limits on Severities of Injuries in Accidents." *Transportation Research Record*: *Journal of the Transportation Research Board* 2083(1), (2008): 122-127.

Malyshkina, Nataliya V. and Fred L. Mannering. "Empirical Assessment of the Impact of Highway Design Exceptions on the Frequency and Severity of Vehicle Accidents." *Accident Analysis & Prevention* 42(1), (2010): 131-139.

Mannering, Fred L. and Chandra R. Bhat. "Analytic Methods in Accident Research: Methodological Frontier and Future Directions." *Analytic Methods in Accident Research* 1, (2014): 1-22.

Mayhew, Daniel R., Herbert M. Simpson, Allan F. Williams, and Susan A. Ferguson. "Effectiveness and Role of Driver Education and Training in a Graduated Licensing System." *Journal of Public Health Policy* 19(1), (1998): 51-67.

Miniño, Arialdi M. "Mortality Among Teenagers Aged 12-19 Years: United States, 1999-2006." *NCHS Data Brief* 37, (2010): 1-8.

Missouri Department of Revenue. *Missouri Graduated Drivers License Law*, 2014. http://dor.mo.gov/drivers/teens/gradlaw.php.

Missouri Traffic Records Committee. *Missouri Uniform Accident Report Preparation Manual*. Missouri State Highway Patrol, 2002.

National Highway Traffic Safety Administration. "Teen Drivers - Graduated Driver Licensing." *NHTSA*. http://www.nhtsa.gov/Driving+Safety/Driver+Education/Teen+Drivers/Teen+Drivers+-+Graduated+Driver+Licensing (accessed January 2012).

Rifaat, Shakil Mohammad, Richard Tay, and Alexandre de Barros. "Effect of Street Pattern on the Severity of Crashes Involving Vulnerable Road Users." *Accident Analysis & Prevention* 43(1), (2011): 276-283.

Rios, Angelyn, Marlena Wald, Sascha R. Nelson, Kimberly J. Dark, Megan Emily Price, and Arthur L. Kellermann. "Impact of Georgia's Teenage and Adult Driver Responsibility Act." *Annals of Emergency Medicine* 47(4), (2006): 369.e1-369.e7.

Savolainen, Peter T., Fred L. Mannering, Dominique Lord, and Mohammed A. Quddus. "The Statistical Analysis of Highway Crash-Injury Severities: A Review and Assessment of Methodological Alternatives." *Accident Analysis & Prevention* 43(5), (2011): 1666-1676.

Savolainen, Peter and Indrajit Ghosh. "Examination of Factors Affecting Driver Injury Severity in Michigan's Single-Vehicle—Deer Crashes." *Transportation Research Record*: *Journal of the Transportation Research Board* 2078(1), (2008): 17-25.

Schneider, William H., Peter T. Savolainen, and Karl Zimmerman. "Driver Injury Severity Resulting from Single-Vehicle Crashes Along Horizontal Curves on Rural Two-Lane Highways." *Transportation Research Record*: *Journal of the Transportation Research Board* 2102(1), (2009): 85-92.

Schneider, William H. and Peter T. Savolainen. "Comparison of Motorcyclist Injury Severity Among Various Crash Types." *Transportation Research Record* 2265, (2011): 70-80.

Shankar, Venkataraman and Fred Mannering. "An Exploratory Multinomial Logit Analysis of Single-Vehicle Motorcycle Accident Severity." *Journal of Safety Research* 27(3), (1996): 183-194.

Shope, Jean T. and Lisa J. Molnar. "Michigan's Graduated Driver Licensing Program: Evaluation of the First Four Years." *Journal of Safety Research* 35(3), (2004): 337-344.

U.S. Department of Health and Human Services, National Insitute of Health. "Graduated Drivers Licensing Programs Reduce Fatal Teen Crashes." *NIH News*, 2011. http://www.nih.gov/news/health/nov2011/nichd-04.htm (accessed November 2011).

Ulfarsson, Gudmundur F. and Fred L. Mannering. "Differences in Male and Female Injury Severities in Sport-Utility Vehicle, Minivan, Pickup and Passenger Car Accidents." *Accident Analysis & Prevention* 36(2), (2004): 135-147.

University of Michigan Transportation Research Institute. "Gradated Driver Licensing - Three Steps to Saving Teens' Lives," 2002.

Williams, Allan F. "Graduated Drivers Licensing Programs Reduce Fatal Teen Crashes." *Institute of Transportation Engineers* 73(9), (2003): 28-30.

Yasmin, Shamsunnahar and Naveen Eluru. "Evaluating Alternate Discrete Outcome Frameworks for Modeling Crash Injury Severity." *Accident Analysis & Prevention* 59, (2013): 506-521.

Ye, Fan and Dominique Lord. "Comparing Three Commonly Used Crash Severity Models on Sample Size Requirements: Multinomial Logit, Ordered Probit and Mixed Logit Models." *Analytic Methods in Accident Research* 1, (2014): 72-85.

APPENDIX A

Current GDL Requirements for Missouri Teenage Drivers
(Missouri Department of Revenue 2014)

Instruction Permit:

Eligible Age: 15
Valid for: 0-12 Months

- You must pass the vision, road sign, and written tests.
- A qualified person must accompany you to the license office to sign a permission statement.
- Under age 16, you may drive only when accompanied in the front seat by a licensed driver who is a qualified person, grandparent, or qualified driving instructor.
- At age 16 or older, you may drive when accompanied in the front seat by a licensed driver who is at least 21 years old and has a valid driver license.
- Seat belts must be worn by the driver and all passengers.
- Your test paper alone is not legal for driving. Be sure to carry your permit with you.
- You may renew your instruction permit.
- You must have an instruction permit for a minimum of 182 days (beginning the day after issuance).
- You may not have any alcohol-related convictions in the last 12 months and no traffic convictions within the last six months.
- You must have received 40 hours of driving instruction, including a minimum of 10 hours of nighttime driving instruction between sunset and sunrise, with a qualified person, grandparent, or qualified driving instructor.

Intermediate License:

Eligible Age: 16 to 18
Valid for: 0-2 Years

- You must hold the instruction permit for at least 182 days (beginning the day after issuance).
- You may not have any alcohol-related offenses in the last 12 months and no traffic convictions in the last six months.
- A qualified person or grandparent must accompany you to the license office to verify you have received 40 hours of driving instruction, including a minimum of 10 hours of nighttime driving instruction between sunset and sunrise.
- You must pass the vision, road sign, and written tests if previous results are more than one year old.
- You must pass the driving test.
- Your test paper alone is not legal for driving. Be sure to carry your intermediate license with you.
- Seat belts must be worn by the driver and all passengers.
- Passenger restrictions outlined below may not be applicable to an intermediate license holder who is operating in agricultural work-related activities.
- During the first six months, you may not operate a motor vehicle with more than one passenger who is under 19 years old and who is not a member of your immediate family.
- After the first six months, you may not operate a motor vehicle with more than three passengers who are under 19 years old and who are not members of your immediate family.
- You may not drive alone between 1:00 a.m. - 5:00 a.m. except to and from a school activity, job, or for an emergency, unless accompanied by a licensed driver 21 years old or older.

To Graduate to an Under-21 Full Driver License:

Eligible Age: 18
Valid for: 0-3 Years

- You must satisfy the requirements for an Intermediate License, including having no alcohol-related offenses or traffic convictions in the last 12 months.
- You must have a valid intermediate license. Your driving privilege cannot be suspended, revoked, or denied when you apply for a full license.
- You must pass the vision and road sign recognition tests. (You are not required to pass the written and driving tests if already completed.)

Jill Bernard *is a Ph.D. candidate in business administration with an emphasis in logistics and supply chain management and a supporting field of marketing at the University of Missouri-St. Louis. She earned a master of business administration degree from Southern Illinois University-Edwardsville, and a bachelor of science degree in business administration with a concentration in marketing from Fontbonne University. Currently, she is a graduate assistant in the Center for Transportation Studies, a Boeing Fellow, a Council of Supply Chain Management Professionals-St. Louis Roundtable board member, and teaches marketing and supply chain courses. Bernard is currently pursuing research interests in the area of motor vehicle traffic safety using traditional and bid data methodologies.*

Donald C. Sweeney II *is a teaching professor of logistics and operations management, an affiliate professor of economics and the associate director of the Center for Transportation Studies at the University of Missouri-St. Louis. He received his Ph.D. in economics from Washington University, St. Louis. His current research interests include the economics of transportation systems, modeling supply chain networks, and the development and use of decision support tools in managing logistics and supply chain networks.*

Equity Evaluation of Sustainable Mileage-Based User Fee Scenarios

by Mark Burris, Sunghoon Lee, Tina Geiselbrecht, Richard Baker and Brian Weatherford

This paper examined equity changes from the imposition of a mileage-based user fee (MBUF) based on how revenue is collected as well as how it is spent. Using the 2009 National Household Travel Survey along with detailed transportation spending estimates, four scenarios were examined. A scenario where an MBUF is combined with a federal tax and includes a greater focus on maintenance spending was the most geographically equitable. Researchers also found that considering funding disbursement when examining the effect of a shift to an MBUF may change the equity of a funding option as compared to only examining revenue source.

INTRODUCTION

The Texas gas tax has been 20 cents per gallon since 1991, and the federal gas tax has been 18.4 cents per gallon since 1993. While the population, number of registered vehicles, and vehicle miles traveled (VMT) in Texas have all increased, funding for transportation has not kept pace due to inflation and the improved fuel efficiency of the vehicle fleet. As a result, while damage to infrastructure has increased due to increased VMT, the money available for maintaining and improving roadways is actually declining (Cho and Powers 2006; Cauchon 2010). Several solutions for increasing revenue have been proposed, such as increasing the gas tax, indexing the gas tax to inflation, expanding toll roads, and increasing the vehicle registration fee. The National Surface Transportation Infrastructure Financing Commission provided several funding options to satisfy growing funding needs but identified a mileage-based user fee (MBUF) as the best long-term strategy (National Surface Transportation Infrastructure Financing Commission 2009). Based on this background, this research will focus on the effect of an MBUF on equity.

The objective of this research is to examine the equity impacts resulting from not only a change in how transportation funding is assessed and collected but also in how it is spent. Several likely funding scenarios were developed, focusing on asset management and environmental sustainability. For example, one scenario directs a much larger portion of revenues to the repair and maintenance of transportation infrastructure than currently planned. Planning documents examined for this effort indicate that funding shortfalls will result in a lower emphasis on maintenance related activities in the state (Texas Department of Transportation 2012a). In fact, there is current consideration to allow lower-functional-classification roads be maintained at a lower pavement score than those in a higher functional class in order to preserve maintenance funds. This research examines the impact of diverting a larger portion of transportation funding to maintenance, relative to current state plans, with respect to geographic equity. Another scenario charges vehicles an MBUF while focusing additional spending on environmentally friendly projects such as transit system expansion projects. Thus, this scenario would entail a significant shift from how revenues are currently spent and could cause considerable equity implications. These were the two primary scenarios examined. These scenarios were compared to using the gas tax for projects as projected in the Texas Department of Transportation's (TxDOT's) unified planning program document (Texas Department of Transportation 2012a). With National Household Travel Survey (NHTS) data for Texas, the change in user fees for travelers under the new fee systems was estimated. By combining this with how the new funding will be allocated, the research determined how much travelers would spend on MBUFs and what

portion of these revenues benefitted them. In this manner, a full picture of the equity impacts, both costs and benefits, was obtained.

The second section of this paper reviews the literature surrounding transportation funding, MBUFs, and equity. The third section examines TxDOT's planned future spending, by category, for the next decade. This research breaks the spending into six categories: 1) urban construction spending, 2) rural construction spending, 3) urban maintenance spending, 4) rural maintenance spending, 5) urban environmental spending, and 6) rural environmental spending. These categories are useful for examining equity when funding amounts shift between these six categories. The fourth section discusses the traveler data obtained from the NHTS. The fifth section discusses the analysis methodology and results from several scenarios examined. Finally, the sixth section contains the conclusions and recommendations based on this research.

LITERATURE REVIEW

This research estimates potential equity changes when the transportation funding method and spending allocations are changed. In this research, the new spending focus area is sustainability, which includes social, economic, and environmental progress of society (Zietsman et al. 2011). Thus, equity (sustainability in terms of social progress and the first of the three areas of social progress) is examined from the perspective of shifts in funding to asset management and protection of the environment (the other two types of societal progress under sustainability). The literature review examines issues surrounding these three concepts of sustainability as well as examining previous MBUF studies.

Sustainability

Sustainability includes a holistic consideration of economic, social, and environmental progress with a long-term perspective (Zietsman et al. 2011). Social progress focuses on social welfare outcomes, such as human health and education attainment, rather than on material wealth, while economic progress is related to the increase of quantity, such as the gross domestic product that measures the quantity but not the quality of market activities (Litman 2009). Environmental progress emphasizes a conservation ethic and policies that reduce any waste of resources such as air, water, and land. The principles of sustainable development have significant implications for allocation of transportation funding because transport activities tend to be resource intensive. Thus, if a sustainable development policy becomes a primary determinant in the allocation of transportation funding, then transportation funds will be used to increase mobility (the economic progress), improve equity (the social progress), and reduce environmental impacts (the environmental progress). For example, the additional funding for more transit projects may reduce the negative environmental impacts from transportation.

An MBUF can change a traveler's behavior by changing travel costs, which in turn can affect energy consumption and emissions for each traveler. Thus, MBUF strategies can be designed to reduce environmental emissions. In addition, the funds can be allocated for environmentally friendly transportation policies such as public transportation and non-motorized modes. The equity impacts of such shifts are the focus of this research.

Asset Management

Transportation asset management is a decision-making procedure for making cost-effective decisions about the design, construction, maintenance, rehabilitation, retrofit, replacement, and abandonment of transportation assets, with the purpose of maintaining or improving the value of these assets over time (Meyer and Miller 2001). In recent years, the national costs of preserving and operating

the current transportation infrastructure, valued at $1.75 trillion, have rapidly increased (U.S. Department of Transportation 2007). If current trends continue, state departments of transportation (DOTs) and other public-sector owners of highway infrastructure will be unable to afford to maintain the transportation system, let alone construct additional capacity (U.S. Department of Transportation 2007). Thus, a transportation asset management strategy may be a primary concern for allocating transportation funds through an MBUF policy. This research examines impacts of increasing the amount of funds spent on maintenance among those aspects of asset management.

Equity of Transportation Expenditure

Equity refers to the distribution of impacts and benefits. Transportation planning and funding decisions have significant and various equity impacts. Transportation equity is commonly classified into two types of equity: horizontal and vertical. Horizontal equity means that same socio-economic status individuals and groups should receive equal shares of resources, bear similar costs, and be treated the same in other ways. On the other hand, vertical equity has to do with the distribution of impacts and benefits among individuals and groups considered different in abilities and needs. These differences may be based on income, social class, transportation ability, and need (Litman 2012). This research focuses on examining horizontal equity with respect to geographic location (urban and rural residents), and vertical equity with respect to household income.

MBUF Research

There are only a handful of studies related to the equity impacts of an MBUF. Burris and Larsen (2012) recently examined potential equity impacts of MBUFs. Their research focused on the equity of funding collection. In their research, Texas data from the 2009 NHTS were used to examine the equity impacts of four MBUF scenarios: 1) flat MBUF scenario, 2) flat MBUF for added revenue scenario, 3) three-tier MBUF scenario to encourage "green" vehicles, which have high fuel efficiencies, and an 4) urban versus rural distinction scenario. In the first scenario, a flat MBUF scenario, the rate of the MBUF was set to recover the same net revenue as the gas tax. In the second scenario, the MBUF rate was increased to raise revenues needed according to a 2030 needs study. In the third scenario, vehicles with high fuel efficiency paid a lower MBUF. In the fourth scenario, since urban roadways and rural roadways have different costs, characteristics, and travelers, rural and urban roadway users were charged a different MBUF. The vertical equity of all MBUF scenarios was similar to the vertical equity of the current Texas gas tax. These results were similar to a previous study of Oregon drivers by Zhang et al. (2009). In terms of horizontal equity, the urban versus rural scenario was more geographically equitable, and a three-tier MBUF scenario to encourage "green" vehicles was found to be the least horizontally equitable. In scenarios 1, , and 4, the horizontal equity was more equitable than the horizontal equity of the current gas tax. Oregon conducted an MBUF pilot study in 2006 (Rufolo and Kimpel 2008). The pilot study compared driver behavior under two scenarios: 1) being charged an MBUF equivalent to the amount paid under the state gas tax, and 2) being charged a higher MBUF during the peak hours and a lower MBUF during the off-peak hours. Over 90% of participants stated that they would agree to replace the current gas tax with an MBUF. This result may not be surprising because the participants already favored the MBUF before the pilot study and thus participated. However, it is still impressive that 90% of participants agreed with the replacement of the gas tax after experiencing the MBUF. The pilot study also found that the MBUF strategy in the second scenario is useful to reduce the VMT during peak hours. Weatherford (2011) evaluated the equity impacts of a flat MBUF using the 2001 NHTS data for the entire United States. His research suggested a rate of 0.98 cents per mile to replace the current federal gas tax. This VMT fee structure would lead to less of a transportation tax burden on low-income households, rural households, and retired households. The result that rural households pay

less under VMT fee structure was similar to results of a previous study by McMullen et al. (2010). However, his research noted that overall changes related to equity are relatively minimal. His research also recommended that any future MBUF scenario needs to consider a policy to promote the use of fuel-efficient vehicles.

DISBURSEMENT OF FUTURE TRANSPORTATION FUNDING IN TEXAS

This section examines estimates of future transportation expenditures for the period 2012 to 2021 and is based on the data from the 2012 Unified Transportation Program (UTP) (Texas Department of Transportation 2012a).

Classification of Future Transportation Expenditures

The future expenditure estimates are classified according to sustainability, as well as the region where the funding is allocated: 1) urban construction spending, 2) rural construction spending, 3) urban maintenance spending, 4) rural maintenance spending, 5) urban environmental spending, and 6) rural environmental spending. Most transportation projects related to economic sustainability are concerned with: (1) the enhancement of travelers' mobility and reduction in travel costs, which can also be viewed primarily in terms of construction projects; and (2) maintenance or asset management projects that economically prolong the useful life of an existing system. Thus, in the above categorization, construction and particularly maintenance spending is related to economic sustainability. Inflation and improved fuel efficiency standards will continue to erode tax revenue for future transportation improvements, so maintenance projects may demand higher portions of the budget just to keep the system operational. For this reason, this research separates construction and maintenance spending. Environmental spending is classified as the spending for transportation projects that aim to improve or preserve the environment even though they accompany either construction or maintenance works. Funding for construction of bike/pedestrian paths and transit rehabilitation and improvement programs is included in our environmental spending category. The geographical distribution, rural versus urban, of future transportation funding is also considered. A review of how detailed spending estimates are provided in terms of geographical boundaries shows the statewide long range transportation plan (SLRTP) (2012c), the Metropolitan Transportation Plan (MTP), the Texas Rural Transportation Plan (TRTP), and UTP use the county boundary. Thus, this research also uses the county boundary to delineate between a rural and urban area. Furthermore, according to the Census Bureau's definition of an urban area (U.S. Census Bureau 2012), if a county has a population greater than 50,000 people and is contained within the metropolitan planning organization (MPO) boundary, this research considers the area to be an urban area. As a result, 54 of the 254 counties within Texas are considered urban areas, and 200 counties are considered rural areas. In 2010, the 54 counties have population of 7,676,751 households (86%) and the 200 counties have 1,246,182 households (14%).

Classification of Future Transportation Expenditure Estimates

The SLRTP (Texas Department of Transportation 2010), UTP (Texas Department of Transportation 2012a), TRTP (Texas Department of Transportation 2012c) and many MPO documents, such as the MTP for the Abilene Metropolitan Planning Organization (Abilene Metropolitan Planning Organization 2010) were selected to estimate statewide long-range transportation expenditure because they provide relatively comprehensive transportation plans over longer periods of time. However, each source had issues regarding the classification of future spending into our six identified categories.

Based on review of the SLRTP, UTP, MTP, and TRTP, this research concluded that the 2012 UTP is the best source to use for statewide future transportation spending estimates. The future spending estimates in the UTP are reclassified into the six categories defined in the previous section. The UTP includes estimates of the total amount of funds spent from 2012 to 2021 for projects in 12 categories, two additional categories, and four programs (Texas Department of Transportation (2012a) for the categories/programs and their spending estimates). Thus, to reclassify the UTP into our six categories, each category/program of the UTP was first split into three categories: 1) maintenance, 2) construction, and 3) environmental. These spending estimates were then divided into rural and urban expenditure. If possible, the split of urban versus rural spending was obtained through the total amount of project expenditures planned for urban and rural areas from a project list of each category/program of the UTP. If that was unavailable, then reliable data sources, such as the District and County Statistics (Texas Department of Transportation 2012b) that include the amount of the current construction and maintenance spending, were used instead. Since MBUFs will be collected from surface transportation modes, Aviation and State Waterways and Coastal Waters Programs are excluded in the analysis. As mentioned in the previous section, all counties within Texas were classified as either rural or urban using both the criteria of 50,000 population and MPO boundary for this analysis. After reviewing a description and the project list of each TxDOT category/program in the UTP, which define characteristics of each category/program, it was classified into our six categories as in Table 1 (see Burris et al. [2013] for details of the classification).

Table 2 provides the total amount of predicted spending in the six categories for the next 10 years (see Burris et. al [2013] for details of the estimates). Most transportation funds (77.6%) will be used in urban areas. Only a small portion of the funds (10.6%) will be used for the transportation projects related to improvement of the environment, whereas 52.0% and 37.4% of the expenditures will be used for maintenance and construction, respectively.

Table 1: Classification of the UTP's Categories/Programs into the Six Categories

Urban Spending		
Construction	**Maintenance**	**Environmental**
• Category 2: Metropolitan and Urban Corridor Projects • Category 3: Non-traditional Funded Transportation Projects • Category 4: Statewide Connectivity Corridor Projects • Category 7: Metropolitan Mobility/Rehabilitation • Category 12: Strategic Priority • Category 8: Prop. 14 Safety Bond	• Category 1: Preventive Maintenance and Rehabilitation • Category 6: Structures Replacement and Rehabilitation • Category 8: Safety • Category 11: District Discretionary	• Category 5: Congestion Mitigation and Air Quality Improvement • Category 9: Transportation Enhancement • Category 10: Supplemental Transportation Projects • Category 10: Earmarks—Fed. Share • Railroad • Transit
Rural Spending		
Construction	**Maintenance**	**Environmental**
• Category 3: Non-traditional Funded Transportation Projects • Category 12: Strategic Priority • Category 8: Prop. 14 Safety Bond	• Category 1: Preventive Maintenance and Rehabilitation • Category 6: Structures Replacement and Rehabilitation • Category 8: Safety • Category 11: District Discretionary	• Category 9: Transportation Enhancement • Category 10: Supplemental Transportation Projects • Category 10: Earmarks—Fed. Share • Railroad • Transit

Source: Burris et al. (2013)

Table 2: Total Predicted Expenditures by Category from 2012 to 2021

Category	Rural	Urban	Total
Maintenance	$5,935,011,162 (20.1%)	$9,403,068,838 (31.9%)	$15,338,080,000 (52.0%)
Construction	$562,715,400 (1.9%)	$10,470,364,600 (35.5%)	$11,033,080,000 (37.4%)
Environmental	$106,509,360 (0.4%)	$3,020,145,640 (10.2%)	$3,126,655,000 (10.6%)
Total	$6,604,235,921 (22.4%)	$22,893,579,079 (77.6%)	$29,497,815,000 (100.0%)

Source: Burris et al. (2013)

The estimates in Table 2 only include the funds for fully approved future projects. The UTP report also includes a total expense forecast. This provides the total future cash flows based on department operations, financial participation by others, and the dollar value of project commitments (Texas Department of Transportation 2012a). Thus, the UTP future spending estimates in Table 2 do not include expenses and projected costs for project development, maintenance, operations, and debt service for new construction projects, and do not take into account all the expenditures and expected payouts from previous projects. However, the UTP does include an item called the total expense forecast. The total expense forecast accounts for these expenditures and is therefore closer to actual future transportation spending estimates. Since a detailed distribution plan for the total expense forecast is not provided, the total expense forecast cannot be directly classified into the six categories used in this research. Therefore, this research allocated the total expense forecast into the six categories in the proportions found in the future spending estimates derived from the UTP. Since the amount spent each year is different, the proportions for 2012 to 2021 are not exactly the same. Next, these proportions were multiplied by the total expenses as outlined in the total expense forecast to determine the total expenditures in each category. Table 3 provides the results of the classification of the total expense forecast into the six categories. Note that these estimates were used in the analysis as the future transportation spending in the six categories.

Table 3: Classification of the Total Expense Forecast into Our Six Categories

Category	2012-2021		
	Rural	Urban	Total
Maintenance	$13,919,430,410 (20.4%)	$22,095,662,077 (32.5%)	$36,015,092,487 (52.9%)
Construction	$1,238,103,049 (1.8%)	$23,523,074,460 (34.6%)	$24,761,177,509 (36.4%)
Environmental	$246,568,254 (0.4%)	$7,032,393,559 (10.3%)	$7,278,961,813 (10.7%)
Total	$15,404,101,713 (22.6%)	$52,651,130,096 (77.4%)	$68,055,231,809 (100.0%)

TRAVEL DATA

The NHTS is a large-scale, nationwide survey that provides planners and researchers with information regarding the travel behavior of Americans, as well as demographic information that may affect travel (U.S. Department of Transportation 2010). The most recent survey (the 2009 NHTS) was conducted from March 2008 to May 2009 and includes over 150,000 households nationwide. One unique feature of the survey is that the data include VMT and fuel efficiency information by household. This feature can be used to estimate each household's tax burden, either under the current gas tax or if an MBUF is implemented. Therefore, gas tax revenue collected either in a specific location (rural or urban area) or from a specific household income class can also be estimated. As a result, the geographical equity and vertical equity of the current gas tax and an MBUF can be estimated. Therefore, this research used data from the 2009 NHTS.

Weighting the 2009 NHTS Data Set

The 2009 NHTS data include a weighting variable that can be used to adjust the new data to better reflect all Texas vehicle-owning households. However, the weights cannot be used in this research without modification because the geographic boundary used by NHTS to divide rural and urban households is different from the boundary that was used to classify transportation spending. This may result in inaccurate analysis of geographical equity when considering a change in the tax system. The 2009 NHTS data set includes a household location variable with households classified as either rural or urban. This variable was categorized by the cartographic boundary that only considers urbanized areas, which consist of the built-up area surrounding a central city with a population density of at least 1,000 people per square mile (U.S. Department of Transportation 2012). This boundary was not consistent with the county boundary used to divide the rural and urban area households for funding as noted in the previous section. Thus, each data set was analyzed to identify the number of households in rural and urban areas.

The 54 urban counties, as defined in the previous section, had a 2010 Census population of 7,676,751 households (86%), while the 200 rural counties had 1,246,182 households (14%) (Texas State Data Center 2013a). Based on the 2009 NHTS data, there were 6,199,869 urban Texas households (78%) and 1,714,454 rural Texas households (22%). The total number of households in the 2010 Census (7,676,751+1,246,182=8,922,933) is also different from the total number of households in the 2009 NHTS data set (6,199,869+1,714,454=7,914,323). The main reason for this difference is that the households in the 2009 NHTS data set modified for this research only represent vehicle-owning households, while the households in the 2010 Census represent all households regardless of vehicle ownership. The two-year difference in when the data were collected may also produce additional differences in the total number of households. The 2010 Census data were the most reliable source and matched the spending data set based on county boundaries, and were therefore used as the true total population. However, the difference in the percentage of rural and urban households between both data sets needs to be considered because the difference is caused by the use of the different boundaries in both data sets. The most ideal method to adjust the difference is to recategorize one data set based on the boundary of the other data set. However, this method could not be applied because the 2009 NHTS data set only mentions whether the household was rural or urban, and not the specific address of a household. Therefore, this research adjusted the ratios of rural and urban NHTS households to match the 2010 Census. For this, the weight variable included in the 2009 NHTS data was adjusted using Equations 1 and 2:

(1) Adjusted Weight of Urban HH

$$= \text{NHTS Weight of Urban HH} \times \frac{\text{Total Number of HHs in NHTS} \times 86\%}{\text{Number of HHs in NHTS in Urban Areas}}$$

$$= \text{NHTS Weight of Urban HH} \times \frac{7{,}914{,}323 \times 86\%}{6{,}199{,}869} = \text{Weight of Urban HH} \times 1.098$$

(2) Adjusted Weight of Rural HH

$$= \text{NHTS Weight of Rural HH} \times \frac{\text{Total Number of HHs in NHTS} \times 14\%}{\text{Number of HHs in NHTS in Rural Areas}}$$

$$= \text{NHTS Weight of Rural HH} \times \frac{7{,}914{,}323 \times 14\%}{1{,}714{,}454} = \text{Weight of Rural HH} \times 0.641$$

Where: HH implies household.

Estimating Future Travel Data from 2012 to 2021

The 2009 NHTS data only provided 2008 travel information for households. However, this research requires future travel data from 2012 to 2021 to estimate tax revenues from either the current gas tax or an MBUF.

Estimating NHTS Weights from 2012 to 2021. Each weight in the previous section reflects the number of vehicles that may have the same travel characteristics in 2008. Thus, the sum of the weights is the same as the total number of vehicles owned by Texas households. Those weights cannot be used for future estimation because the number of vehicles in Texas will change in the future. Thus, new weights for future travel need to be estimated. However, projections for vehicle increase rates classified by the household location (rural and urban areas) in Texas for the future are not available. Thus, to estimate the number of vehicles during 2012 to 2021, this research first estimates past vehicle increases in both rural and urban areas between 2001 and 2007 (Texas Department of Transportation 2013). Then, this research also considered past population increases in both rural and urban areas between 2001 and 2007 (Texas State Data Center 2013b) because the change in population generally reflects the change in the number of vehicles. From these two estimations, the relationship between population growth and the increase in the number of vehicles between 2001 and 2007 was estimated (see Table 4). Using this relationship and projected future populations (Texas State Data Center 2013c), the projection for vehicle increase rates was estimated. This projection was applied to the NHTS weighting factors.

Table 4: Relationship Between Vehicle Increase and Population Increase

	(a) Vehicle Increase Rate	(b) Population Increase Rate	Ratio (a/b)
Rural areas	17.30%	3.90%	4.44
Urban areas	20.17%	13.57%	1.49
All of Texas	19.68%	12.10%	1.63

Estimating Fuel Efficiency Improvements. The current gas tax is charged in proportion to the amount of fuel consumed. The amount of fuel consumed in each household can be calculated by dividing the VMT of each household vehicle by the fuel efficiency (in MPG) of the vehicle. The 2009 NHTS data included these VMT and MPG estimates of each household vehicle in 2008. However, the average fuel efficiency is expected to increase in the future. This will reduce the gas tax burden of each household and Texas gas tax revenue because the amount of fuel consumed will decrease. Castiglione et al. (2011) provides the projections of average MPG for all vehicles in Texas that were used in the Transportation Revenue Estimator and Needs Determination System (TRENDS) model (Castiglione et al. 2011). The vehicle in the NHTS data set had its fuel efficiency increased using the projections.

Estimating Fuel Costs. The 2009 NHTS data included the cost of fuel (dollars per gallon) that each household paid for one gallon of gasoline in 2008. A shift to the MBUF will cause a change in fuel prices because the tax will be subtracted from the total fuel price. This change may also affect the VMT of households—as fuel price increases, VMT is generally reduced. This effect of fuel price change on VMT due to the shift to MBUFs was considered in this research. Thus, estimates of fuel cost for each household from 2012 to 2021 are also required. For the fuel cost estimates in 2012, historical data of average gasoline prices in Texas between 2008 and 2012 were used to estimate the increase (U.S. Energy Information Administration 2013). For the future fuel cost estimates from 2013 to 2021, this research assumes that the cost of fuel for each household will change at the same

rate as nationwide gasoline prices. Thus, projected U.S. gasoline price changes from 2013 to 2021 were used (U.S. Department of Transportation 2009).

MBUF AND FUNDING DISBURSEMENT SCENARIOS

To evaluate the equity of an MBUF, this research considers the change in revenue collection as well as the disbursement of funds. Table 5 provides a brief description of the scenarios. Note that all monetary estimates in this section are expressed in 2012 dollars and apply a 4% inflation rate.

Table 5: Brief Description of the Scenarios

Scenario	Gas Tax System	Funding Disbursement
Scenario 1	Current state and fed. gas tax	Same as the current disbursement
Scenario 2 (static and dynamic)	Flat MBUF and fed. gas tax	Same as the current disbursement and increased revenue by the MBUF
Scenario 3 (static and dynamic)	Flat MBUF and fed. gas tax	More disbursement to maintenance spending
Scenario 4 (static and dynamic)	Flat MBUF and fed. gas tax	More disbursement to environmental spending

Static Versus Dynamic Scenarios

Revenue that will be collected from the MBUF in the future is estimated assuming no change in driver behavior due to the MBUF (static) and a change in VMT due to the MBUF (dynamic). To estimate the change in VMT due to the MBUF for the dynamic scenario, reasonable values of elasticity (ratio of percent change in VMT to percent change in total cost of gas and MBUF) are required. However, since MBUF research is still in the theoretical stage, empirical elasticities of VMT and the associated price of gas/MBUF cannot be directly estimated. Thus, this research adopted the values of elasticity used in previous MBUF research (Burris and Larsen 2012) (see Table 6). Note that these values were derived from Wadud et al. (2009) and are based on the price elasticity of gas. These elasticities were used to calculate the anticipated change in annual VMT for households within each subcategory disaggregated by household income level and geographic location. Elasticities are based on the percent change in the total price of gas, not just the change in the state gas tax portion of the price.

Table 6: Price Elasticities by Household Income Level and Geographic Location

Household Income Level ($1,000s)	Urban Households	Rural Households
<20	−0.447	−0.254
20–40	−0.280	−0.159
40–60	−0.259	−0.147
60–100	−0.335	−0.191
100+	−0.373	−0.212
Total (weighted average)	−0.339	−0.192

Source: Burris and Larsen (2012)

Scenario Structure

All scenarios are structured based on two perspectives, revenue collection and transportation funding disbursement. The revenue here implies the total expected Texas revenue from either the current gas tax (both state and federal) or the MBUF along with the federal gas tax. The disbursement of transportation funds reflects possible changes in future funding disbursement, including distribution of increased revenue due to the MBUF, additional disbursement to maintenance spending, and additional disbursement to environmental spending.

Scenario 1. Scenario 1 evaluates the equity of the current plans. This includes the revenue that will be collected from the current gas tax together with the current planned transportation funding disbursement from 2012 to 2021. To calculate the revenue estimates from 2012 to 2021, it is assumed that there will be no changes in the state (20 cents/gallon) or federal (18.4 cents/gallon) gas tax from 2012 to 2021. Annual revenues were calculated by multiplying the VMT of all Texas (adjusting for future growth) vehicles by 38.4 cents/gallon and dividing by each vehicle's fuel efficiency adjusting for the change in fuel efficiency. This scenario uses the current funding disbursement plan from 2012 to 2021 shown in Table 3.

Scenario 2. In Scenario 2, the state gas tax is replaced with a flat MBUF to estimate revenue. In addition, static models (no change in driver behavior due to the MBUF) and dynamic models (a change in VMT due to the MBUF) are considered. A shift from the current state gas tax to the MBUF will increase projected revenues since fuel efficiencies are increasing while total VMT is increasing. Thus, for the funding disbursement in this scenario, increased revenue due to the MBUF was distributed into our six categories. To estimate revenues from 2012 to 2021, this research first determined a flat MBUF that would generate roughly the same gross revenue in 2012 as the current state gas tax. The amount of revenue in 2012 from the current state gas tax was $1,662,386,960 based on the weighted NHTS data. The total VMT of the Texas households was 190,854,877,961 miles in 2012 based on the weighted NHTS data. Thus, the rate of flat MBUF in the static model was determined as $0.008710/mile ($1,662,386,960/190,854,877,961 miles). The next step was to determine an MBUF associated with the dynamic model. The change in total VMT in 2012 due to the MBUF was estimated to be -280,782,179 miles based on the elasticity of demand in Table 6. Thus, the flat MBUF in the dynamic model was determined to be $0.008723/mile ($1,662,386,960/190,574,095,782 miles). In addition, in dynamic Scenario 2, changes in VMT due to the MBUF ($0.008710/mile) were also considered for every year from 2013 to 2021 to estimate the revenue from 2013 to 2021 because the weights, fuel costs, and fuel efficiencies were different for each year. This research assumed that the rate of the federal gas tax will not change. In addition, similar to Burris and Larsen's research (2012), 80% of urban household travel was assumed to be on urban roadways, and 20% of urban household travel was assumed to be on rural roadways. Thus, 80% of the MBUF revenue collected from urban households was considered revenue for urban areas, and 20% of the MBUF revenue was considered revenue for rural areas. Conversely, 80% of the MBUF revenue collected from rural households was considered revenue for rural areas, and 20% of the MBUF revenue was considered revenue for urban areas. For funding disbursement scenarios, this research assumes that changes to funding disbursements begin in 2017 because planning for future transportation projects, including environmental reviews, public input, and funding allocation, takes many years. Table 7 provides the increased revenues from 2017 to 2021 due to the MBUF in the static model and in the dynamic model. The increased revenue each year was distributed to the six categories with the same average proportions from 2012 to 2021 found in Table 3. Finally, those additional revenues were then added to the annual spending amounts.

Table 7: Increased Revenues due to the MBUF

Model	2017	2018	2019	2020	2021
Static	$170,502,196	$204,966,508	$239,905,768	$275,517,439	$312,050,777
Dynamic	$165,612,994	$199,298,088	$233,544,599	$268,502,718	$303,825,899

Scenario 3. If the current transportation funding shortfalls are not improved, construction spending may be shifted to maintenance spending to maintain the current transportation infrastructure, rather than be used to construct new infrastructure. Scenario 3 was designed to consider this change in funding disbursement focus, whereas the same revenue structure as in Scenario 2 was applied to this scenario. This scenario also assumed that the funding disbursement focus can only be changed from 2017 to 2021. For the funding disbursement in this scenario, this research assumed that 50% of construction spending for each year from 2017 to 2021 estimated in Scenario 2 would be shifted to maintenance spending in the future. To distribute this shifted construction expenditure in each year into rural maintenance and urban maintenance expenditure for each year, the average proportions of rural maintenance and urban maintenance spending from 2012 to 2021 was used. The environmental funding disbursement is not changed in this scenario.

Scenario 4. This scenario was designed to be an environmentally friendly transportation spending policy change. Similar to Scenario 3, the same revenue structure as in Scenario 2 was applied to this scenario. If a transportation policy focus moves to an environmentally friendly policy, it stands to reason that transportation funding allocation will reflect this policy. Thus, for the funding disbursement in this scenario, this research assumed that 50% of planned construction spending for each year from 2017 to 2021 estimated in Scenario 2 would be shifted to environmental projects. To distribute the shifted construction funds in each year into rural environmental and urban environmental expenditure for each year, the average proportions of rural environmental and urban environmental spending from 2012 to 2021 were applied. The amount spent on maintenance was not changed in this scenario.

Results

Revenue. The total revenue estimates from 2012 to 2021 for rural and urban areas is provided in Table 8. As previously mentioned, the rate of the MBUF was set so that it would generate the same revenue in 2012 that was generated by the current gas tax. However, it was expected that the MBUF would generate more total revenue over all 10 years of analysis. This is primarily related to the expected fuel efficiency improvement of vehicles. Texas households will consume less fuel due to fuel efficiency improvements, thereby paying less in gas taxes under the current gas tax system. In addition, rural areas would contribute a higher percentage of total revenue under the MBUF system relative to the current tax system. These results were partially caused by the 80/20 assumption illustrated in Scenario 2. Since an MBUF charges based on miles driven, rural areas will generate more revenue, while urban areas will generate less. It is reasonable that the total revenue in the dynamic model is a little less than the revenue in the static model because the total VMT is reduced due to elasticity of demand.

In Scenario 4, as transit infrastructure increases due to the increased environmental spending, total VMT in Texas may decrease because automobile trips may be replaced by transit trips. However, most residents in Texas depend heavily on automobile trips. As a result, a relatively small amount of spending for transit service is currently planned for the next 10 years. This amount is $395,875,000 and this accounts for 12.7% of total predicted environmental expenditure in Table 2. Thus, even though the environmental spending will be increased, most spending will be allocated to reduce negative environmental impacts of automobile trips, such as the "Clean Technology Revolving Loan Program" in Dallas, rather than to increase transit service. Thus, reduction in total VMT due

to the transit service would be minimal. For this reason, this research did not consider the reduction in total VMT to estimate revenue in Scenario 4.

Table 8: 2012 to 2021 Revenue Estimates for Each Scenario

Scenario	Rural	Urban	Total
Current tax (for Scenario 1)	$5,417,437,003 (20%)	$21,557,187,519 (80%)	$26,974,624,522
MBUF and fed. tax—static (for static Scenarios 2, 3, and 4)	$7,553,595,698 (26%)	$20,965,267,325 (74%)	$28,518,863,023
MBUF and fed. tax—dynamic (for dynamic Scenarios 2, 3, and 4)	$7,546,981,882 (27%)	$20,929,622,877 (73%)	$28,476,604,759

Disbursement. This research assumed that transportation funding will be distributed into six categories with different amounts allocated to each category based on the scenarios examined. Thus, the total funding disbursements from 2012 to 2021 for each category depend on the scenarios and are compared in Table 9. As expected, the biggest amount of rural maintenance and urban maintenance spending is allocated in both static and dynamic Scenario 3. Rural environmental spending does not largely increase even in Scenario 4, the environmentally friendly funding disbursement scenario, in terms of dollar amount. This is because environmental spending is mainly used for urban areas in the current transportation plan. Since the revenue does not largely increase due to the MBUF, the total amount of funds available in Scenario 1 is not much smaller than that in the other scenarios. Table 10 provides the total funding disbursement estimates from 2012 to 2021 in urban and rural areas. Allocating a greater percentage of funds to maintenance in Scenario 3 results in an increase in the amount of funds directed to rural areas. However, even if Scenario 4 has a greater percentage of environmental spending, the proportions of rural and urban disbursements are similar to Scenarios 1 and 2.

Table 9: Comparison of Funding Disbursements in Millions of Dollars

Category	R-M	U-M	R-C	U-C	R-E	U-E	Total
Scenario 1	13,919	22,096	1,238	23,523	247	7,032	68,055
Static Scenario 2	14,165	22,486	1,260	23,939	251	7,157	69,258
Dynamic Scenario 2	14,159	22,476	1,259	23,928	251	7,153	69,227
Static Scenario 3	15,688	24,903	1,125	20,134	251	7,157	69,258
Dynamic Scenario 3	15,679	24,890	1,125	20,129	251	7,153	69,227
Static Scenario 4	14,165	22,486	1,125	20,134	384	10,963	69,258
Dynamic Scenario 4	14,159	22,476	1,125	20,129	384	10,954	69,227

Note: R-M = rural maintenance spending. U-M = urban maintenance spending. R-C = rural construction spending. U-C = urban construction spending. R-E = rural environmental spending. U-E = urban environmental spending.

Table 10: Estimates of Funding Disbursement for Each Scenario

Scenario	Rural	Urban	Total
Scenario 1	$15,404,101,715 (23%)	$52,651,130,096 (77%)	$68,055,231,811
Static Scenario 2	$15,676,384,257 (23%)	$53,581,790,241 (77%)	$69,258,174,498
Dynamic Scenario 2	$15,669,251,996 (23%)	$53,557,412,215 (77%)	$69,226,664,211
Static Scenario 3	$17,063,880,985 (25%)	$52,194,293,513 (75%)	$69,258,174,498
Dynamic Scenario 3	$17,054,819,865 (25%)	$52,171,844,346 (75%)	$69,226,664,211
Static Scenario 4	$15,674,651,449 (23%)	$53,583,523,049 (77%)	$69,258,174,498
Dynamic Scenario 4	$15,667,611,638 (23%)	$53,559,052,573 (77%)	$69,226,664,211

Revenue Compared to Disbursement. The ratio of revenue (Table 8) to disbursement (Table 10) was estimated to simultaneously examine both the burden and the benefit for each area (see Table 11). For example, for static Scenario 2, the ratio of rural area was estimated by dividing $15,676,384,257 in Table 10 by $7,553,595,698 in Table 8 and the ratio of urban area was estimated by dividing $53,581,790,241 in Table 10 by $20,965,267,325 in Table 8. The ratios were 2.075 and 2.556, respectively. For dynamic Scenario 2, the ratio of rural area was estimated by dividing $15,669,251,996 in Table 10 by $7,546,981,882 in Table 8 and the ratio of urban area was estimated by dividing $53,557,412,215 in Table 10 by $20,929,622,877 in Table 8. The ratios were 2.076 and 2.559, respectively. Since differences between static and dynamic scenario ratios are very small, this research expresses them as a two-decimal-point value without distinguishing static and dynamic scenarios in Table 11. A larger ratio means that the area received more funding than its tax burden. This ratio should, in theory, be close to one. However, the revenue includes only the gas tax from household gasoline-run vehicles, while expenses are based on all kinds of revenue (such as gas tax, registration fee, fare revenue, and lubricant tax). Therefore, the ratio estimates were much greater than one. Comparison of the ratios across the areas gives a rough idea about the geographical equity of the gas tax and funding disbursement. That is, a smaller difference between the ratios in both areas implies more geographical equity. Thus, Scenario 3, where the MBUF combined with the federal tax focuses on maintenance funding disbursement, is the most geographically equitable transportation policy. Whereas, Scenarios 2 and 4 are the least geographically equitable. Across the scenarios, Scenario 1 is the most beneficial for rural areas.

Table 11: Ratios (Disbursement/Revenue) and Their Rank in Each Scenario

Scenario	a) Rural (Rank)	b) Urban (Rank)	Difference (b-a)
1	2.84 (1st)	2.44 (4th)	−0.40
2 (static and dynamic)	2.08 (4th)	2.56 (1st)	0.48
3 (static and dynamic)	2.26 (2nd)	2.49 (3rd)	0.23
4 (static and dynamic)	2.08 (4th)	2.56 (1st)	0.48

Note: The rank is ordered by the largest ratio across the scenarios.

Geographical Equity. This research estimated two types of geographical equity (equity between rural and urban areas) with respect to funding disbursements to reflect two perspectives of equity. The first one is equity based on the number of urban and rural households, and the second is equity based on the percentage of revenues collected from each area.

To begin, the percentage of funds spent on rural and urban areas was compared to the percentage of (vehicle owning) households in rural and urban areas. In this measure, the closer the ratio is to one, the more equitable the funds spent are. This is because one area receives an appropriate amount of funds corresponding to its number of households. Scenario 3, with its focus on maintenance,

proved to be the least equitable (see Table 12). This is because a larger percentage of maintenance funding is used for rural areas compared with the percentage of rural households.

Secondly, the percentage of funds spent on rural and urban areas was compared to the percentage of revenues collected from rural and urban areas. When considering the percentage of revenue in each area instead of the percentage of households, the geographical equity of the disbursement was different from the results in Table 12. All scenarios are geographically equitable based on the values of the ratios — all the ratios are relatively close to one (see Table 13). Scenarios 2 and 4 are slightly less equitable than the current gas tax (Scenario 1). Scenario 3 was slightly more equitable than the current gas tax.

Table 12: Geographical Equity of the Disbursement Based on Percentage of Households

Scenario	Percentage of Funds Spent in Rural Areas	Percentage of HHs in Rural areas	Ratio of Funds to HHs (Rank, 1=Most and 4=Least Equitable)
1	22.6%	14.0%	1.6 (1st)
2 (static and dynamic)	22.6%	14.0%	1.6 (1st)
3 (static and dynamic)	24.6%	14.0%	1.8 (4th)
4 (static and dynamic)	22.6%	14.0%	1.6 (1st)

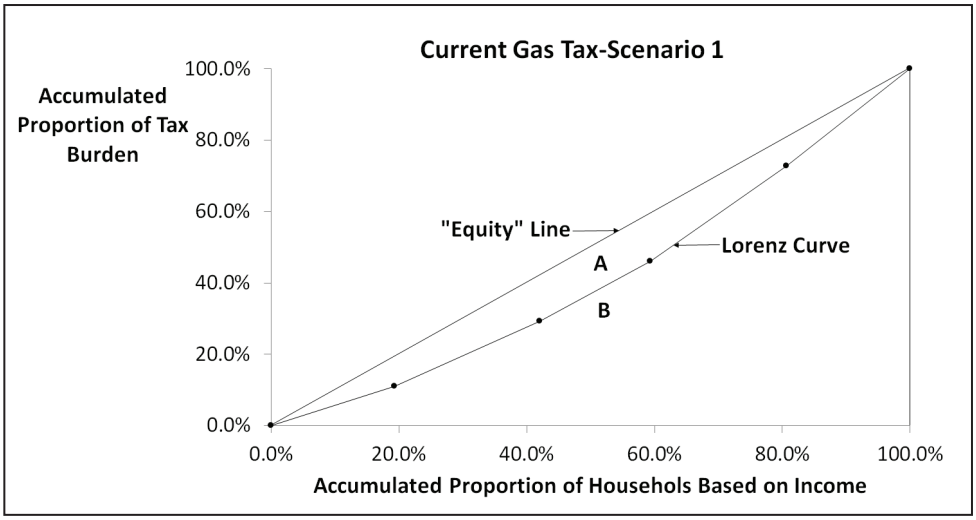
Table 13: Geographical Equity of the Disbursement Based on Percentage of Revenues

Scenario	Percentage of Funds Spent in Rural Areas	Percentage of Revenues Collected from Rural areas	Ratio of Funds to Revenues (Rank, 1=Most and 4=Least Equitable)
1	22.6%	20.1%	1.13 (2nd)
2 (static and dynamic)	22.6%	26.5%	0.85 (4th)
3 (static and dynamic)	24.6%	26.5%	0.93 (1st)
4 (static and dynamic)	22.6%	26.5%	0.85 (4th)

Vertical Equity. To estimate vertical equity of the revenues, Gini coefficients were calculated. Gini coefficients and Lorenz curves (see Figure 1) are common quantitative and visual methods, respectively, used to evaluate equity. The closer the Lorenz curve is to the equity line, the more equitable the tax is across household incomes. According to Drezner et al. (2009), "The Gini coefficient (G) is the ratio of the area between the Lorenz curve and the straight equity line to the entire area below the equity line." The value of a Gini coefficient can range from zero to one, with zero indicating complete equality and one indicating complete inequality (Rock 1982). Gini coefficients can be calculated using equation 3:

$$(3) \quad G = \frac{A}{A + B}$$

Figure 1: Lorenz Curve Plot for Tax Burden (Scenario 1)



The vertical equity of the current gas tax and the MBUF combined with the federal tax, without consideration of funding disbursement, was examined. To plot the Lorenz curves for the Gini coefficients, the percentage of households based on income class were plotted on the x-axis, and the percentage of tax burden in each household income class was plotted on the y-axis. The results in Table 14 show that the vertical equity of the current gas tax is basically identical to that of the MBUF. This is because the rate of the MBUF in this research was determined as a rate that would generate roughly the same net revenue in 2012 as the current gas tax.

Table 14: Gini Coefficients of Tax Burden Based on Household Income

Scenario	Gini Coefficients
Current tax (for Scenario 1)	0.1690
MBUF and fed. tax—static (for static Scenarios 2, 3, and 4)	0.1694
MBUF and fed. tax—dynamic (for dynamic Scenarios 2, 3, and 4)	0.1694

This research adopted the 2012 unified transportation program (UTP) for estimates of spending. In the UTP, each category has different projects, and therefore has been separated by TxDOT. However, some categories are highly related to each other in terms of their project characteristics, such as Category 2 and Category 5. Thus, in the future, there is a high possibility that spending for one category is shifted to another category. As a result, equity will be affected by this relationship.

In our research, Scenarios 3 and 4 assume that 50% of planned construction spending would be shifted to maintenance and environmental spending. The amount of the shifted funding was about $4 billion. Even though we shifted this large amount of funding, the equity of Scenarios 3 and 4 changed only a small amount (see Table 11). From these results, even if some spending for one category was shifted to its related category, equity will not be largely affected because the amount of the spending would be much less than the 50% of the construction spending.

CONCLUSIONS AND RESEARCH LIMITATIONS

Through this research, potential equity impacts of shifts in revenue collection and spending were examined. Four different scenarios were examined to evaluate equity impacts due to these changes during the years 2012 to 2021. The first scenario analyzed was the current state gas tax and the current

funding disbursement. In the other scenarios, equity impacts of funding disbursement changes were analyzed under a situation where the MBUF replaces the state gas tax. Two types of geographical equity related to funding disbursements were examined. The first one is geographical equity of funding disbursement based on the percentage of urban and rural households. Scenario 3, where the MBUF is combined with the federal tax and focuses more on maintenance funding disbursement, was the least equitable because rural areas receive a larger percentage of the funding compared with the number of rural households. The second is geographical equity of funding disbursement based on the percentage of revenues collected from each area. In this measure, Scenario 3 was the most equitable. Through the results of these two measures, it was clear that the equity of a transportation funding disbursement policy depends on how it is measured. The first measure, the geographic equity of the funding disbursement based on the percentage of urban and rural households, can be used to examine a policy that aims to provide equal benefits based on the geographic location of the population. The second measure, the geographic equity of the funding disbursement based on the percentage of tax collected from each area, is useful to examine a policy that aims to distribute funding in relation to how much an area paid in taxes. Lastly, the vertical equity was examined using the Gini coefficient. The current state plus federal gas tax is similar in vertical equity to that of the MBUF combined with the federal tax for all scenarios.

Through these analyses, researchers found that considering funding disbursement when examining the effect of a shift to the MBUF may change the equity of different scenarios compared with when funding disbursement is not considered. If the MBUF rate is set at the same level as the current tax, a shift to the MBUF would have little impact on vertical equity. However, geographic equity would be reduced by the MBUF based on the revenue estimates because a shift to the MBUF increases the percentage of tax burden for rural areas. This negative impact can be alleviated by changing the funding disbursement focus; in this research, allocating more funding to maintenance improved geographical equity.

Due to the inherent difficulties of 10-year predictions for both revenue and funding disbursement estimates, several assumptions were made in performing this analysis. First, we assumed the decrease in construction spending to be 50% in Scenarios 3 and 4, but this was an arbitrary value and changing this value would affect the results. Additionally, the funding disbursement plan for the next 10 years is not perfectly clear because a few transportation plans for some categories/programs are not decided. In addition, since this research used the NHTS data set, only household gasoline-run vehicles were included in the analysis under the assumption that vehicles dependent on a different source of energy accounted for only a small portion of all household vehicles. Commercial vehicles registered in each area were not considered in this research. In the scenarios where the MBUF is implemented, the breakdown of road-type travel by both urban households and rural households was assumed to be 80/20 based on Burris and Larsen's (2012) research. This assumption can greatly affect the results. Thus, a more reliable value is required in future research. Lastly, the vertical equity of the gas taxes could not be considered together with funding disbursement because this research did not analyze how disbursement varies by income group. Based on the knowledge gained from this research, examining the vertical equity of the gas tax with consideration of funding disbursement to each income class may provide different results and be worth investigating.

Acknowledgments

This research was performed under a grant from the U.S. Department of Transportation University Transportation Centers Program for the Southwest University Transportation Center, which is funded, in part, with general revenue funds from the State of Texas and funding from the Texas Department of Transportation (TxDOT). The authors are grateful for their support. The authors also appreciate the support from TxDOT in helping them access and compile the vast amount of data on

budget allocation for projects in Texas. Comments from anonymous reviewers were also helpful in the preparation of this final paper. All omissions and errors are the sole responsibility of the authors.

References

Abilene Metropolitan Planning Organization. *Abilene Metropolitan Area Transportation Plan 2010–2035*, 2010.

Burris, M. and L. Larsen. *Equity Evaluation of Vehicle Miles Traveled Fees in Texas*. South West University Transportation Center, College Station, Texas, 2012. http://swutc.tamu.edu/publications/technicalreports/161105-1.pdf.

Burris, M., S. Lee, T. Geiselbrecht, and T. Baker. *Equity Evaluation of Sustainable Mileage-based User Fee Scenarios*. South West University Transportation Center, College Station, Texas, 2013. http://swutc.tamu.edu/publications/technicalreports/600451-00007-1.pdf.

Castiglione, J., R.D. Ellis, and B. Glover. *The Transportation Revenue Estimator and Needs Determination System (TRENDS) Model*. Texas A&M Transportation Institute, College Station, Texas, 2011.

Cauchon, D. "Gas Taxes Give Us a Break at the Pump." *USA Today*, July 2, 2010.

Cho, A. and E.M. Powers. "Investors and Voters are Willing to Pay to Pave U.S. Highways." *ENR: Engineering News-Record* 256(2), (2006): 24-28.

Drezner, T., Z. Drezner, and J. Guyse. "Equitable Service by a Facility: Minimizing the Gini Coefficient." *Computers and Operations Research* 36(12), (2009): 3240–3246.

Litman, T. "Sustainable Transportation Indicators: A Recommended Research Program for Developing Sustainable Transportation Indicators and Data." Presented at 88th Annual Meeting of the Transportation Research Board, Washington, D.C., 2009.

Litman, T. *Evaluating Transportation Equity*. Victoria Transport Policy Institute, Victoria, 2012. http://www.vtpi.org/equity.pdf (accessed May 16, 2012).

McMullen, S., L. Zhang, and K. Nakahara. "Distributional Impacts of Changing from a Gasoline Tax to a Vehicle-mile Tax for Light Vehicles: A Case Study of Oregon." *Transport Policy* 17, (2010): 359-366.

Meyer, M.D. and J.E. Miller. *Urban Transportation Planning—Section 4.2.3 Evolution Toward Asset Management*, 2nd ed. McGraw-Hill, New York, (2001): 190–191.

National Surface Transportation Infrastructure Financing Commission. *Paying Our Way: A New Framework for Transportation Finance*. Report of the National Surface Transportation Infrastructure Financing Commission, 7-8, 202, 2009.

Rock, S.M. "Applying the S-Index to Transportation Financing Alternatives." *Transportation Research Record*: *Journal of the Transportation Research Board* 858, (1982): 36–39.

Rufolo, A.M. and J.T. Kimpel. "Responses to Oregon's Experiment in Road Pricing." *Transportation Research Record*: *Journal of the Transportation Research Board* 2079, (2008): 1–7.

Texas Department of Transportation. *Texas Statewide Long-Range Transportation Plan 2035, 2010*. http://www.txdot.gov/government/reports/statewide-2035.html.

Texas Department of Transportation. *2012 Unified Transportation Program (UTP)*, 2012a. http://ftp.dot.state.tx.us/pub/txdot-info/fin/utp/2012_utp_052611.pdf.

Texas Department of Transportation. *District and County Statistics*, 2012b.http://www.txdot.gov/inside-txdot/division/finance/discos.html.

Texas Department of Transportation. *The Texas Rural Transportation Plan*, 2012c. http://www.txdot.gov/inside-txdot/division/transportation-planning/rural-2035.html.

Texas Department of Transportation. *Statistics*, 2013. http://www.txdot.gov/txdot_library/publications/stats.htm.

Texas State Data Center. "Table 23: 2010 Household Size, Average Household Size, and Average Family Size for Texas and Texas Counties," 2013a. http://txsdc.utsa.edu/Data/Decennial/2010/SF1/Descriptive.aspx.

Texas State Data Center. *Texas Population Estimates Program*, 2013b. http://txsdc.utsa.edu/Data/TPEPP/Estimates/Index.aspx.

Texas State Data Center. *Texas Population Projections Program*, 2013c. http://txsdc.utsa.edu/Data/TPEPP/Projections/.

U.S. Census Bureau. *2010 Census Urban and Rural Classification and Urban Area Criteria*. U.S. Department of Commerce, Washington, D.C, 2012. http://www.census.gov/geo/reference/ua/urban-rural-2010.html.

U.S. Department of Transportation, Federal Highway Administration. *Asset Management: Overview*, 2007. http://www.fhwa.dot.gov/asset/if08008/assetmgmt_overview.pdf (accessed May 15, 2012).

U.S. Department of Transportation, National Highway Traffic Safety Administration. *Corporate Average Fuel Economy for MY 2011 Passenger Cars and Light Trucks*, 2009. http://www.nhtsa.gov/DOT/NHTSA/Rulemaking/Rules/Associated%20Files/CAFE_Final_Rule_MY2011_FRIA.pdf (accessed June 8, 2013).

U.S. Department of Transportation, Federal Highway Administration. *NHTS, National Household Travel Survey: Our Nation's Travel*, 2012. http://nhts.ornl.gov/introduction.shtml#implementation (accessed June 13, 2013).

U.S. Department of Transportation, Federal Highway Administration. *FAQ—Urban-Rural Designations*, 2012. http://nhts.ornl.gov/2009/pub/Urban%20Rural%20FAQ.pdf.

U.S. Energy Information Administration. "Weekly Retail Gasoline and Diesel Prices," 2013. http://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_stx_a.htm.

Wadud, Z., D.J. Graham, and R.B. Noland. "Modelling Fuel Demand for Different Socio-Economic Groups." *Applied Energy* 86(12), (2009): 2740-2749.

Weatherford, B.A. "Distributional Implications of Replacing the Federal Fuel Tax with Per Miles User Charges." *Transportation Research Record*: *Journal of the Transportation Research Board* 2221, (2011): 19–26.

Zhang, L., S. McMullen, D. Valluri, and K. Nakahara. "Vehicle Mileage Fee on Income and Spatial Equity." *Transportation Research Record*: *Journal of the Transportation Research Board* 2115, (2009): 110-118.

Zietsman, J., T. Ramani, J. Potter, V. Reeder, and J. DeFlorio. NCHRP Report 708: *A Guidebook for Sustainability Performance Measurement for Transportation Agencies*. Transportation Research Board, National Research Council, Washington, D.C, 2011.

Mark W. Burris *is a professor in the Zachry Department of Civil Engineering at Texas A&M University, and a research engineer at the Texas A&M Transportation Institute. Burris's main area of interest is traveler behavior in response to pricing, particularly congestion (or value) pricing. He has been, and continues to be, involved in many projects in this area and has published extensively in this area of research. Prior to joining Texas A&M, he was a senior research associate at the Center for Urban Transportation Research in Tampa, Florida. Burris is a member of the Institute of Transportation Engineers and chair of the Transportation Research Board's Transportation Economics committee.*

Sunghoon Lee *is pursuing a Ph.D. in transportation engineering in the Zachry Department of Civil Engineering at Texas A&M University, and is a graduate research assistant at the Texas A&M Transportation Institute. His main research interests are traveler's behavior in response to cost of travel and social benefits of transportation infrastructures. Lees's current research focuses on estimating the social benefits of managed lanes on the Katy Freeway in Houston.*

Tina Geiselbrecht *is an associate research scientist and has more than 15 years of applied research experience. She heads the Public Engagement Planning program at TTI and has led or contributed to numerous research projects across several topics. Her primary interest is public outreach to inform transportation policy decisions. She has been the lead researcher on several projects that have explored public opinion through the use of stakeholder interviews and focus groups. Geiselbrecht holds a bachelor of arts degree in economic geography from the University of Texas at Austin and a master's of applied geography and planning from Texas State University. She is a member of the American Association of Public Opinion Researchers and certified by IAP2 – International Association for Public Participation.*

Richard T. Baker *is an assistant research scientist with the Texas A&M Transportation Institute's Mobility Management program located in Austin, Texas. His primary research interests relate to transportation funding, finance, policy, and public acceptance. He received a bachelor's degree in political science and a master of public administration degree from Texas A&M University. Baker was named as TTI's New Researcher of the Year in 2010.*

Brian A. Weatherford *is a senior fiscal and policy analyst with the California Legislative Analyst's Office. He earned his Ph.D. in policy analysis from the RAND Graduate School in 2012. While at RAND, Weatherford investigated the distributional equity implications of mileage-based user fees.*

Is the Decision to Code-Share a Route Different for Virtual and Traditional Code-Share Arrangements

by Yan Du and B. Starr McMullen

This paper analyzes factors that determine whether alliance carriers choose to remain in or leave a code-share agreement on individual routes. Different types of code-sharing are considered: traditional code-shared routes, virtual code-shared routes and those routes with both traditional and virtual code-sharing. Empirical results show that factors affecting alliance firms' code-sharing decisions significantly differ for virtual versus traditional code-share agreements. Virtual code-sharing tends to take place in less dense markets and is not significantly affected by yields. This provides tentative support for the Ito and Lee (2005) argument that virtual code-sharing provides a mechanism by which carriers practice price discrimination (for instance, filling unoccupied seats in less dense markets). In contrast traditional code-sharing is found to be more likely to occur in dense markets and higher yields increase the probability of such arrangements. Thus, traditional code-sharing seems to be used to achieve the networking economics and cost savings derived from dense markets and thus appears to be more effective as an instrument to introduce competition into a market.

INTRODUCTION

Code-sharing, a phenomenon originally observed in international airline markets, emerged as a popular and important form of alliance in the U.S. domestic airline industry in the mid-1990s. Considerable research has focused on the impact of code-sharing on air fares, passenger volumes, and consumer welfare either in the international or U.S. domestic airline markets (Brueckner 2001, 2003; Brueckner and Whalen 2000; Hassin and Shy 2004; Oum, Park and Zhang 1996; Park 1997; Park and Zhang 2000; Park, Park, and Zhang 2003; Park, Zhang, and Zhang 2001; Bamberger, Carlton, and Neumann 2004; Armantier and Richard 2006, 2008; Du, McMullen, and Kerkvliet 2008; Heimer and Shy 2006; Gayle 2008).

However, Ito and Lee (2005, 2007) have suggested that it may be important to distinguish between traditional code-sharing and virtual code-sharing. Whereas traditional code-sharing typically refers to combining the networks of two distinct operating carriers, virtual code-sharing involves a single operating carrier and a marketing carrier that differs from the operating carrier.[1] Ito and Lee (2005) argue that the majority of the U.S. domestic code-sharing fit the definition of virtual code-sharing. They find that fares in virtual code-share markets tend to be lower than pure online or traditional code-share fares. This leads them to hypothesize that virtual code-sharing is used by carriers as a means of product differentiation rather than as a means to enter markets and exploit profitable opportunities as usually thought for traditional code-share arrangements. They argue that the customer of an individual carrier may place a greater value on that carrier's service; thus the price that consumers are willing to pay for a pure online Continental flight for instance, which is both operated and marketed by Continental may be higher than the price for the same flight if marketed by America West. The fact that some frequent flyer programs may not count the flight if it is marketed by a code-share partner makes the incentive for virtual code-sharing even stronger.

To provide more information on the motivation for entering into virtual rather than traditional code-share arrangements on individual routes, this paper extends a recent study by McMullen and Du (2012) in which the determinants of route level participation in the America West and Continental code-share agreement were examined. McMullen and Du (2012) find the decision to enter into code-

sharing on a route was positively influenced by the yield, alliance firm hub dominance, booking frequencies, and vacation routes; code-sharing was less probable when the route was concentrated and when there was airport congestion. However, in that study there was no distinction made between traditional and virtual code-shared routes.

The purpose of this paper is to see whether the decision to enter into code-sharing on a route is significantly different for virtual and traditional code-shared routes. If virtual code-sharing is used more as a tool for product differentiation as hypothesized by Ito and Lee (2005, 2007), the decision to virtually code-share a route may depend on different factors than those for traditional code-share arrangements. In that case, it may be appropriate for government regulators to consider the nature of code-sharing (virtual or traditional) first when considering the possible competitive implications of such arrangements.

BACKGROUND

The America West and Continental code-share arrangement, which spanned the 1994-2002 period, was the first domestic code-share alliance between U.S. carriers and was one of the longest lasting domestic code-share agreements When this arrangement started, America West Airlines was the second largest low-cost air carrier in the U.S. (later operating as U.S. Airways) and was one of deregulation's greatest successes. However, rapid expansion without proper handling of large operating losses placed the company at the verge of bankruptcy, and rising fuel prices due to instability in the Persian Gulf finally led America West to file for bankruptcy in 1991. In 1994, America West was able to secure reorganization resulting in a large portion of the airline being owned by a partnership with Continental Airlines. This ultimately resulted in the code-shared arrangement with Continental and heralded the beginning of code-sharing alliances for the domestic U.S. airline industry. Previous to this agreement, code-sharing had been used extensively in international markets but not on solely domestic routes.

Although the America West-Continental code-share agreement went into effect in 1994, data are only available from 1998Q1 to 2002Q4.[2] Throughout the arrangement, firms continually reassessed their decision to code-share on individual routes and then changed their code-share arrangements accordingly (McMullen and Du 2012).

EMPIRICAL HYPOTHESES AND VARIABLE DEFINITIONS

In this paper, we focus only on code-shared routes that involve one-stop flight service. Compared with non-stop or multi-stop flights, a one-stop flight through a code-share arrangement is more comparable to a pure online flight (operated by a single carrier) that has one stop. Due to the limitations of our data set, we include only routes on which Continental and America West code-shared for at least one quarter during the1998-2002 sample period. On some routes, code-sharing began at the very start of the alliance agreement and lasted for the entire alliance period, while on other routes, code-sharing occurred for a time period after which the route was dropped. Sometimes a route was added and dropped several times during the alliance period, whereas others were code-shared for one quarter and then dropped forever.

To account for all these circumstances, we assume firms make their code- sharing decisions at the beginning of each quarter for each route. Thus, our dependent variable is a qualitative response variable that represents the code-share decision. The dependent code-share decision variable $DECISION_{it}$ is valued at 1if alliance firms engaged in code-sharing on that route during period t and valued at 0 if there was no code-sharing on the route during period t.

We assume the density of the dependent variable $DECISION_{it}$ follows an exponent distribution with the probability of code-sharing denoted as π_{it}. The classical logistic regression model is then specified as

$$(1)\quad \log\left(\frac{\pi_{it}}{1-\pi_{it}}\right) = f(\beta_0, X) + \varepsilon_{it}$$

Where X is a matrix of the explanatory variables that includes characteristics of both incumbents and alliance firms' flight operations as well as those of relevant routes and airport markets.

Finally, we include the same set of explanatory variables used by McMullen and Du (2012) to control for route specific characteristics on each route. This allows us to compare the results found when no distinction is made between the two types of code-share arrangements (traditional and virtual) to results for each type of code-sharing separately. Accordingly, the matrix of explanatory variables, X, includes the following:

Average Yield. $YLD_{i,t-1}$ is defined as the average price per passenger mile on route i in the previous quarter t-1. Average price is calculated as the weighted average of per passenger air fares from all carriers operating in the market. For traditional code-sharing we expect higher average yields from the previous period to increase the probability of code-sharing because high yields indicate high profitability from a code-sharing alliance.

Booking Frequencies. $FRE_{i,t-1}$ is defined as the number of bookings by incumbent carrier customers on route i in the previous time period, t-1. This is used as a proxy for flight frequency, which was not available for this data set. It is hypothesized that increases in flight frequency indicate higher potential market demand that results in a greater probability of entry into code-sharing. Note that both $FRE_{i,t-1}$ and $YLD_{i,t-1}$ are lagged one period to avoid any potential endogeneity.

Route Level Competition Level. $RHHI_{i,t-1}$ is defined as Herfindahl Hirschman Index (HHI) on route i at time t-1. HHI is calculated using the number of passengers carried by individual carriers on a specific route. If high concentration creates an effective barrier to entry, this may make code-sharing less likely on routes with a high HHI. However, if profits are high on high HHI routes and code-sharing is an easier way to enter than entering with new service, code-sharing may be more likely to occur. Thus, the overall effect of route competition level on the probability of code-sharing is uncertain.[3]

Population. POP_{it} is defined as the product of the populations at the endpoints of the Metropolitan Statistical Areas (MSAs) on route i at time t. This is a proxy for the potential market size, and we expect that a larger population will lead to higher travel demand and thus a higher probability of code-sharing.

Per Capita Income. $INCO_{it}$ is defined as the product of the per capita income for MSAs at endpoints of route i at time t. We expect higher per capita income to result in higher air travel demand and therefore a greater probability of code-sharing.

Vacation Dummy. VAC_i was set equal to 1 if one of the endpoint airports was in Florida, Hawaii, Nevada, or Puerto Rico, otherwise it is equal to 0. We expect the sign to be positive as vacation routes will generate more passengers than non-vacation routes, all other factors being equal.

Hub Dummies for Code-shared Firms. If either the endpoint airports ($ORIHUB_i$ and $DESTHUB_i$) or the connecting airport ($CONHUB_i$) are hubs for code-shared firms, then the dummy variable takes a value of 1. These variables are chosen to capture the benefits carriers may obtain from economies of traffic density on their hub-and-spoke network systems. We expect that the alliance firm hubs at either endpoint or at the connecting airport may increase the probability of code-sharing on the route. Table A1 in the Appendix provides a list of hubs for all major carriers in the United States during this study time period.

Slot Control Dummy. $SLOT_i$. During the time period for this study, the USDOT had limits set on the number of takeoffs and landings that could take place in any given hour period at four airports: Chicago, O'Hare; New York, J.F. Kennedy and La Guardia; and Washington, Reagan National

Airport. If either end point or connecting airport is a slot-controlled airport, then $SLOT_i$ equals 1 otherwise 0. A negative coefficient is expected, indicating that the presence of slot controls reduces the probability of code-sharing.

Gate Constraints Dummy. $GATE_i$. In addition to slot controls, there were six airports (Charlotte, Cincinnati, Detroit International, Minneapolis, Newark, and Pittsburgh) in which long-term, exclusive use gates are thought to create barriers to entry (USGAO 1993). If either the endpoint or connecting airport is a gate-constrained airport, then $GATE_i$ equals 1 otherwise 0. We assume code-sharing will be deterred in the airports with gate constraints due to airport congestion (Dresner, Windle, and Yao 2002).

Quarterly Dummies. WIN_t, SPR_t, SUM_t were used to control for seasonal fixed effects on air travel demand.

Time. $TIME_t$ measures the longevity (in years) of the initial code-sharing alliance. For instance, if the code-share route arrangement began in 1994, then $TIME_t$ = 5 in year 1998, 6 in year 1999, 7 in year 2000, 8 in year 2001, and 9 in year 2002. The expected sign of the time coefficient is ambiguous. On one hand, the longer firms stay in an alliance, the better the reputation of the alliance and the lower the continuation cost, suggesting a positive relationship between $TIME_t$ and the probability of code-sharing. However, as time passes, market situations may change dramatically, firms' financial situations and operating strategies may change, government policy may change, and experience in the market may either increase or decrease the attractiveness of code-sharing.

DATA

Our complete data sample has 55,120 quarterly observations on a total of 2,756 routes that were code-shared by Continental and America West Airlines at some time during 1998Q1 to 2002Q4 period. Among the 2,756 code-shared routes, 1,113 (or 40%) of routes were purely traditional code-shared routes (TCS), 793 (or 29%) of routes were purely virtual code-shared (VCS) and 850 (or 31%) of routes contained both traditional and virtual code-shared segments (TVCS). Every observation is route and time specific. Table 1 shows the descriptive statistics.

The data for the number of passengers and per passenger air fares for individual carriers on route i at time t are from the U.S. Department of Transportation (USDOT), Bureau of Transportation Statistic's (BTS) Origin and Destination Survey DB1B Market, a 10% ticket random sample data set. YLD_{it} is calculated as the average price per passenger mile on route *i* at time *t* where average price is calculated as the weighted average of the per passenger air fare for all air carriers operating on that route. The data for the code-sharing decision $DECISION_{it}$ are collected by tracking each route that was ever code-shared by Continental and America West Airlines, quarter by quarter. The data for the number of booking frequencies $FLTS_{it}$ and the calculation of route concentration $RHHI_{it}$ are from DB1B Market. Hub dummies are identified from each air carrier's website.[4] The data for population POP_ORIGIN_{it} and POP_DEST_{it} and per capita income $INCOME\_ORIGIN_{it}$ and $INCOME\_DEST_{it}$ at origin and destination airport MSAs are from the U.S. Department of Commerce, Bureau of Economic Analysis (BEA). The slot control and gate constraints dummies are obtained from reports by the U.S. General Accounting Office (1993).

Table 1: Descriptive Statistics

Variables (Descriptions and Units)	Mean	Std Dev
$DECISION_{it}$ (Equals 1 if the alliance firms code-shared on route *i*, otherwise 0)	0.1884	0.391
YLD_{it-1} (Average air fare from *t-1* in dollars per passenger mile in the one-stop market of route *i*)	0.0676	0.027
FRE_{it-1} (All incumbent customers' booking frequencies from *t-1* on route *i*)	421	337
$RHHI_{it-1}$ (HHI from *t-1* in the one-stop market of route *i*)	2739	1507
$INCOME\_ORIGIN_{it}$ (Per capita income in dollars at the MSA of the origin airport on route *i*)	18126	3262
$INCOME\_DEST_{it}$ (Per capita income in dollars at the MSA of the destination airport on route*i*)	18082	3288
POP_ORIGIN_{it} (Population at the MSA of the origin airport on route *i*)	4061988	4654822
POP_DEST_{it} (Population at the MSA of the destination airport on route *i*)	4075897	4667366
$SLOT_i$ (Equals 1 if either the endpoint or the connecting airport is slot-controlled)	0.0722	0.2589
$GATE_i$ (Equals 1 if either the endpoint or the connecting airport has gate constraints)	0.2496	0.4328
VAC_i (Equals 1 if either the endpoint or connecting airport on route *i* is in FL, HI or NV; otherwise 0)	0.3792	0.4852
$ORIHUB_i$ (Equals 1 if the origin airport on route *i* is the alliance firms' dominated hub or focus city)	0.3266	0.469
$CONHUB_i$ (Equals 1 if the connecting airport on route *i* is the alliance firms' dominated hub or focus city)	0.8545	0.353
$DESTHUB_i$ (Equals 1 if the destination airport on route *i* is the alliance firms' dominated hub or focus city)	0.3193	0.4662
WIN_t (Equals 1 if the quarter is in Jan-Mar; otherwise 0)	0.25	0.433
SPR_t (Equals 1 if the quarter is in Apr-Jun; otherwise 0)	0.25	0.433
SUM_t (Equals 1 if the quarter is in Jul-Sep; otherwise 0)	0.25	0.433
TCS_i (Equals 1 if the route was once traditionally code-shared; otherwise 0)	0.7123	0.453
VCS_i (Equals 1 if the route was once virtually code-shared; otherwise 0)	0.5962	0.4907
$TIME_t$ (Equals 5 if in year 1998, 6 in 1999, 7 in 2000, 8 in 2001, 9 in 2002)	7	1.414

All the dollar values are deflated by Consumer Price Index (1982-84=100).

ECONOMETRIC MODELS AND EMPIRICAL RESULTS

Following Molenberghs and Verbeke (2005) for the study of discrete longitudinal data, we apply subject-specific models for the analysis of the discrete longitudinal data set, in which the dependent variable is non-Gaussian repeated binary measures.[5]

In subject-specific models, when responses are binary, the effect of covariates on the response probabilities is conditional upon the level of the subject-specific effect. A unit change in the covariate translates into an appropriate change in probability, keeping the level of the subject-specific effect fixed (Neuhaus, Kalbfleisch, and Hauck 1991). Although subject-specific parameters can be dealt

with either as fixed or random effects, the fixed effects approach is subject to criticism due to possible inconsistency of the so-obtained maximum likelihood estimates. Therefore, we follow McMullen and Du (2012) and use Generalized Linear Mixed Models (GLIMM) estimated using Penalized Quasi-likelihood (PQL) methods from Breslow and Clayton (1993), the most frequently used random effects model in the context of discrete repeated measurements.[6,7,8]

We apply the GLIMM methodology to four different regression scenarios: the first regression duplicates the McMullen and Du (2012) pooled sample of all 2,756 code-shared routes in which there is no distinction between the TCS, VCS, or TVCS types of code-sharing. The additional three regressions are run on three mutually exclusive subsets of this pooled data set, namely: the 1,113 pure traditional code-shared (TCS) routes, the 793 purely virtual code-shared (VCS) routes, and the 850 routes that involved both traditional and virtual code-sharing (TVCS). We then compare the regression results to see whether there are differences in the importance of specific variables affecting the decision to enter into a TCS differ versus a VCS arrangement.

Table 2 compares the fixed effect parameter estimates from the GLIMM regression in the four different regressions. More detailed regression results and a comparison of standardized coefficients from the GLIMM regression on the pooled routes, TCS, VCS and TVCS routes are provided in Appendix Table 4 and 5.[9]

GLIMM regression results for the TVCS sample are very similar to those reported for the pooled sample of code-share routes as in McMullen and Du (2012). The main difference is that the route level concentration as measured by the Herfindahl Hirschman Index (HHI) does not have a significant impact on the decision to engage in this TVCS kind of code-shared route.

The first notable difference between the TCS and VCS results is that higher yields have a positive and significant impact on the decision to engage in a TCS arrangement, but no significant effect at all upon the decision to engage in a VCS arrangement.[10]

Consistent with the McMullen and Du (2012) results for the pooled sample, route concentration level, as measured by HHI, significantly deters code-sharing entry on both TCS and VCS routes.[11] While airport congestion, measured by slot control (SLOT) and gate constraints (GATE), have significant and negative coefficients in the pooled sample and SLOT also significantly reduces TCS, for VCS routes neither congestion measure has a statistically significant coefficient.[12] A vacation route significantly affects the probability of code-sharing in the pooled sample and on the TCS routes but not on the VCS routes. This result supports the hypothesis that vacation routes generate more passengers than non-vacation routes, therefore increasing the probability of code-sharing. Carriers choose to traditionally code-share on vacation routes because of the potential route density.

The significant and negative coefficients for INCO and POP for VCS routes show that carriers engage in VCS arrangements in less dense, less congested, and lower income markets. These results provide further evidence that VCS routes are not being used to generate more passengers, but to allow segmentation of the passengers in the market that is necessary for price discrimination, supporting Ito and Lee's (2005, 2007) argument that VCS routes serve to price discriminate rather than as a mechanism for firms to compete with each other in the market.

On a specific route, as found in the pooled sample, hub dominance at the end point or connecting airports positively and strongly affects the probability of code-sharing on the TCS routes. On the VCS routes, only hub dominance at the connecting airport (CONHUB) has a significant impact on the probability of code-sharing. Hub dominance at the origin (ORIHUB) or destination (DESTHUB) does not affect alliance firms' virtual code-share decisions.[13] This difference between code-share decisions for TCS and VCS routes reflects alliance firms' marketing strategies: carriers may take advantage of hub dominance to exercise market power and extract monopoly rents through traditional code-share agreements. However, hub-dominated airports where economies of scale or traffic density can be achieved are not necessarily the top priority for virtual code-sharing.

Table 2: Comparison of GLIMM Regression Results in Different Scenarios on Pooled, TCS, VCS or TVCS Routes

	Pooled Routes	TCS Routes	VCS Routes	TVCS Routes
INT	**-1.04****** (-6.01)	**-1.56****** (-7.83)	**2.51****** (8.11)	**-.84***** (-2.32)
$FLTS_{i,t-1}$	**3.07E-04****** (3.3)	1.74E-04 (1.53)	-5.32E-05 (-.35)	**7.35E-04****** (4.49)
$YLD_{i,t-1}$	**14.38****** (16.36)	**6.82****** (7.8)	1.11 (.69)	**26.39****** (14.58)
$RHHI_{i,t-1}$	**-1.70E-04****** (-9.17)	**-4.12E-05****** (-2.33)	**-1.21E-04****** (-3.16)	-5.44E-05 (-1.14)
$INCO_{it}$	**7.54E-04***** (2.2)	-3.1E-04 (-.92)	**-3.9E-03****** (-6.52)	**4.1E-03****** (6.04)
POP_{it}	**2.09E-03***** (2.12)	8.00E-04 (.65)	**-3.3E-03***** (-2.1)	1.99E-03 (1.14)
$SLOT_i$	**-1.28****** (-11.2)	**-.60****** (-4.25)	0.06 (.43)	**-2.04****** (-7.9)
$GATE_i$	**-.27****** (-4.07)	-0.06 (-.93)	-0.05 (-.46)	**-.59****** (-4.54)
VAC_i	**.44****** (7.67)	**.11**** (1.88)	0.06 (.73)	0.16 (1.42)
$ORIHUB_i$	**.86****** (13.71)	**0.40****** (6.56)	-0.07 (-0.63)	**1.01****** (8.53)
$CONHUB_i$	**1.53****** (16.84)	**0.41****** (4.74)	**0.37****** (2.75)	**1.63****** (7.86)
$DESTHUB_i$	**0.90****** (14.49)	**0.30****** (4.52)	0.06 (.59)	**1.05****** (8.9)
TIME	**-0.55****** (-52.1)	**-0.24****** (-13.6)	**-0.57****** (-24.8)	**-0.78****** (-45.8)
WIN_t	**0.46****** (12.61)	**0.14***** (2.08)	**0.60****** (7.86)	**0.64****** (11.47)
SPR_t	**0.25****** (6.67)	**0.13***** (1.96)	**0.17***** (2.14)	**0.38****** (6.83)
SUM_t	-0.05 (-1.43)	-0.08 (-1.13)	-0.01 (-0.07)	-0.07 (-1.26)

***p*=0.1 level; ****p*=0.05 level; *****p*=0.01 level.

As time passes, the probability of code-sharing tends to decrease significantly in every scenario though the impact level is different. The odds of code-sharing decrease by 43% on a VCS route and by 22% on a TCS route as one more year passes.[14] This implies that alliance firms tend to end the virtual code-sharing more easily than the traditional one as time passes, which only makes sense since a VCS arrangement involves no actual deployment of resources to operate flights and thus is easier to enter or exit.

Finally, alliance firms tend to code-share in the winter and spring on TCS, VCS, TVCS routes and the pooled sample. Summer, as well, does not significantly affect any type of code-sharing. This is because code-sharing helps generate traffic in off-seasons such as winter, spring, and fall, whereas the travel demand is usually seasonally high in the summer, leading to smaller incentives to code-share.

CONCLUSIONS

Our empirical results show that code-sharing decisions are influenced by different factors for virtual (VCS) versus traditional (TCS) code-shared routes. The decision to engage in a traditional code-share arrangement is significantly influenced by average yield from previous period, slot controls, whether the route is a vacation route, and hub dominance at both the connecting and endpoint (origin and destination) airports. These same factors do not appear to be important determinants of the decision to engage in virtual code-sharing. While income and population were not found to be significant determinants of the decision to engage in traditional code-sharing, higher incomes and populations significantly lower the probability of virtual code-sharing. Finally, greater route concentration as measured by the Herfindahl Index significantly lowers the probability of code-sharing for both traditional and virtual code-shared routes.

Overall, these findings imply that virtual code-sharing tends to take place in less dense markets, which may not support many carriers or flights, in contrast to traditional code-sharing, which is undertaken to achieve the networking economics and cost savings derived from dense markets. These results support Ito and Lee's (2005, 2007) argument that virtual code-sharing is used by alliance firms as a generic or qualitatively inferior product to further segment customers between those who are willing to purchase the branded premium product (pure on-line ticket) and those who are not. VCS fares are generally lower than TCS fares and also lower than fares on routes where no code-sharing occurs (the operating carrier is the same as the ticketing carrier for the entire route). Thus, code-sharing may provide the airline a way to practice price discrimination on a flight to fill up seats without losing revenue by having to lower fares for all customers.

From the perspective of government agencies or policy makers, the distinction between traditional and virtual code-sharing may have important implications for policy. Virtual code-sharing takes place in less dense markets and is not significantly affected by yields, therefore does not appear to be a mechanism by which carriers compete with each other for market share but rather allows a carrier that is already providing service on a route to fill up planes in less dense markets. Traditional code-sharing seems to be more effective as an instrument by which competition is introduced into a market as higher yields in a market definitely increase the probability of such arrangements. However, the results here show that although code-sharing may help increase competition in markets by inducing entry when prices are high, such entry, either by traditional or virtual code-share arrangements, is significantly impeded by high market concentration on the route. Therefore, monitoring competitive conditions on the VCS routes to insure against the possible exercise of market power in the alliance carriers' hubs (or focus cities) are not as important as for the TCS routes, though government agencies should be alert for anti-competitive behavior on the part of market incumbents on highly concentrated TCS or VCS routes.

Acknowledgements

This research is funded by College Research Grant 2012-13 of Beijing Normal University-Hong Kong Baptist University United International College (BNU-HKBU UIC) under financial code R201324. The authors wish to thank participants in paper sessions at the 88th Western Economic Association International Conference (WEAI) for helpful comments and suggestions.

Endnotes

1. For example, a virtual code-share itinerary may consist of a connection between two Continental flights (CO: CO) or two America West flights (HP: HP) while the entire ticket is marketed or sold by America West (HP: HP) or Continental Airlines (CO: CO), respectively. Virtual code-sharing could also occur on a direct flight itinerary if the operating carrier was CO or HP but the marketing carrier was HP or CO, respectively. If the operating carrier is Continental on both segments of an itinerary (CO: CO) but one segment of the ticket is sold by America West

while the other segment is sold by Continental (CO: HP or HP: CO), then the itinerary is called semi-virtually code-shared. Even though under virtual code-sharing, the marketing carrier does not receive any operating revenue other than a nominal commission, it benefits from a more frequent flight schedule due to its larger virtual network provided by the operating carrier.

2. Information on code-shared routes between Continental and America West is available from Bureau of Transportation Statistics (US Department of Transportation) only from 1998 because of reporting requirements adopted by the Congress in 1998.

3. All these three covariates $YLD_{it\text{-}1}$, $FRE_{it\text{-}1}$, and $RHHI_{it\text{-}1}$, are the moving averages in the past four quarters from *t-1* to *t-4* to smooth out the seasonal effect on these variables.

4. We also use the number of flights, yield, and route HHI calculated from the direct service market or the whole market, which includes direct, one-stop and multi-stop services on a route as the covariates, but the parameter estimates are strongly insignificant.

5. In longitudinal settings, each individual has a vector of responses with a natural (time) ordering among the components. Non-Gaussian longitudinal cases include repeated binary or ordinal data, or longitudinally measured counts.

6. Neyman and Scott (1948) show that in a fixed-effect model, if the number of subjects is getting larger while the number of time points remains constant, the number of parameters is increasing at the same rate as the sample size, which leads to inconsistency of the so-obtained maximum likelihood estimates. This is a well-known result in the context of logistic regression for binary data.

7. Let Y_{it} be the *t*th outcome measured for subject *i*, *i*=1, …, *N*, *t*=1, …, t_i and Y_i is the t_i dimensional vector of all measurements available for subject *i*. The GLIMM model is then formalized as $Y_{it} \mid b_i -- Bernoulli(\pi_{it})$ where random effects b_i are assumed to be drawn independently from the *N (0, G)* and the responses Y_{it} of Y_i are independent with densities of an exponential distribution. The conditional means $E(Y_{it} \mid b_i)$ are given by $E(Y_{it} \mid b_i) = \frac{\exp(\beta_0 + b_i + \beta X)}{1+\exp(\beta_0 + b_i + \beta X)}$ which can be rewritten as $\log it(\pi_{it}) = \log(\frac{\pi_{it}}{1-\pi_{it}}) = \beta_0 + b_i + \beta X$ where $\pi_{it} = P(Y_{it} = 1|b_i, X)$, β_0 is the constant term, and β is a *p*-dimensional vector of unknown fixed regression coefficients, common to all subjects.

8. The density of an exponential distribution for Y_{it} takes the form as follows $f_i(y_{it} \mid b_i, \beta, \phi) = \exp\{\phi^{-1}[y_{it}\theta_{it} - \varphi(\theta_{it})] + c(y_{it}, \phi)\}$ with ϕ a scale parameter, i.e. $\eta(\mu_{it}) = x_{it}^{'}\beta + z_{it}^{'}b_i$ for a known link function η(.), and for x_{it} and z_{it} two vectors containing known covariates. The density of the *N (0, G)* distribution for the random effects b_i is denoted as $f(b_i \mid G)$.

9. Standardized coefficients are the estimates resulting from an analysis performed on variables that have been standardized so that they have variances of 1. It is usually used to answer the question of which of the independent variables has a greater impact on the dependent variable in a multivariate regression analysis, when the variables are measured in different units of measurement.

10. On the TCS routes, the odds of code-sharing increase 98% for every increase of 0.1 dollar in the yield. The calculation is as follows: 1.98-1=0.98, in which 1.98 is the odds of code-sharing for the variable average yield ($YLD_{it\text{-}1}$). Please refer to the odds for different variables provided in Appendix Table A2. The calculation of odds for other variables follows the same way.

11. Please refer to Table A2 in the Appendix. For every increase of 1,000 in the value of HHI, the odds of code-sharing decrease by 4% on TCS routes (0.96-1 = -0.04 = -4%, in which 0.96 is the odds ratio of code-sharing for the variable $RHHI_{it-1}$) but only 0.01% on VCS routes. (0.9999 -1 = -0.0001 = -0.01%, in which 0.9999 is the odds ratio of code-sharing for the variable $RHHI_{it-1}$.)

12. See Table A2 in the Appendix. The odds ratio of code-sharing on a slot-controlled TCS route is only 0.55 times the odds on a TCS route without slot-control.

13. See Table A2 in the Appendix. On the TCS routes, the impact of the hub airports is smaller than in the pooled sample: the odds ratios of code-sharing when the origin, connecting, and destination airports are hubs (or focus cities) are 1.49, 1.50, and 1.34 times (compared with 2.35, 4.6, and 2.47 in the pooled sample) the probability of code-sharing when none of the airports is a hub (or focus city), respectively. By contrast, the odds ratio of code-sharing is 1.45 times the probability if the connecting airport is not a hub on the VCS route.

14. Please refer to the odds for different variables provided in Table A2 in the Appendix. The calculation is as follows: 0.57-1 = -0.43 = -43% and 0.78-1 = -0.22 = -22%, in which 0.57 and 0.78 are the odds ratios of code-sharing for the variable TIME on the VCS and TCS routes, respectively.

References:

Armantier, O. and O. Richard. "Evidence on Pricing from the Continental Airlines and Northwest Airlines Code-Share Agreement." D. Lee ed. *Advances in Airline Economics* 1, Elsevier Publisher (2006): 91-108.

Armantier, O. and O. Richard. "Domestic Airline Alliances and Consumer Welfare." *Rand Journal of Economics* 39 (3), (2008):875-904.

Bamberger, G.E., D.W. Carlton, and L.R. Neumann. "An Empirical Investigation of the Competitive Effects of Domestic Airline Alliances." *Journal of Law and Economics* 47, (2004):195-222.

Breslow, N.E. and D.G. Clayton. "Approximate Inference in Generalized Linear Mixed Models." *Journal of the American Statistical Association* 88, (1993): 9-25.

Brueckner, J.K. "The Economics of International Code-sharing: An Analysis of Airline Alliances." *International Journal of Industrial Organization* 19, (2001): 1475-1498.

Brueckner, J.K. "International Airfares in the Age of Alliances: The Effects to Code-sharing and Antitrust Immunity." *Review of Economic Statistics* 85, (2003): 105-118.

Brueckner, J.K. and W.T. Whalen. "The Price Effect of International Airline Alliances." *Journal of Law and Economics* 43, (2000): 503-544.

Dresner, M., R. Windle, and Y. Yao. "Airport Barriers to Entry in the US," *Journal of Transport Economics and Policy* 36(2), (2002), 389-405.

Du, Y., B.S. McMullen, and J. Kerkvliet. "The Economic Impact of the ATA/Southwest Airlines Code-share Agreement." *Research in Transportation Economics* 24 (1), (2008): 51-60.

Gayle, P.G. "Airline Code-share Alliances and Their Competitive Effects." *Journal of Law and Economics* 51(4), (2008): 743-766.

Hassin, O. and O. Shy. "Code-sharing Agreements and Interconnections in Markets for International Flights." *Review of International Economics* 12(3), (2004):337-352.

Heimer, O. and O. Shy. "Code-sharing Agreements, Frequency of Flights, and Profits Under Parallel Operation. "*Competition Policy and Antitrust* (2006): 163-181.

Ito, H. and D. Lee. "Domestic Codesharing Practices in the US Airline Industry." *Journal of Air Transport Management* 11, (2005):89-97.

Ito, H. and D. Lee. "Domestic Code Sharing, Alliances, and Airfares in the U.S. Airline Industry." *Journal of Law and Economics* 50, (2007): 355-380.

McMullen, B.S. and Y. Du. "Determinants of Successful Code-Sharing: A Case Study of Continental and America West Airlines Alliances – A Discrete Longitudinal Analysis." James Peoples ed. *Advances in Airline Economics*, *Volume 3*. Emerald Group Publishing Ltd (2012): 157-175.

Molenberghs, G. and G. Verbeke. *Models for Discrete Longitudinal Data*. Springer Science & Business Media, Inc. New York, 2005.

Neuhaus, J.M., J.D. Kalbfleisch, and W.W. Hauck. "A Comparison of Cluster-specific and Population-averaged Approaches for Analyzing Correlated Binary Data." *International Statistical Review* 59, (1991): 25-35;

Neyman, J. and E.L. Scott. "Consistent Estimates Based on Partially Consistent Observations." *Econometrica* 16, (1948): 1-32.

Oum, T.H., J.H. Park, and Y. Zhang. "The Effects of Airline Code-sharing Agreements on Firm Conduct and International Air Fares." *Journal of Transport Economics and Policy* 30(2), (1996): 187-202.

Park, J.H. "The Effects of Airline Alliances on Markets and Economic Welfare." *Transportation Research Part E: Logistics and Transportation Review* 33(3), (1997):181-195.

Park, J.H., N.K. Park, and A. Zhang. "The Impact of International Alliances on Rival Firm Value: A Study of the British Airways US Air Alliance."*Transportation Research Part E: Logistics and Transportation Review* 39(1), (2003): 1-18.

Park, J.H. and A. Zhang. "An Empirical Analysis of Global Airline Alliances: Cases in North Atlantic Markets." *Review of Industrial Organization* 16, (2000): 367-383.

Park, J.H., A. Zhang, and Y. Zhang. "Analytical Models of International Alliances in the Airline Industry." *Transportation Research Part B: Methodological* 35(9), (2001): 865-886.

U.S. Department of Commerce, Bureau of Economic Analysis (BEA), "Regional Data." http://www.bea.gov/iTable/iTable.cfm?reqid=70#reqid=70&step=1&isuri=1

U.S. Department of Transportation (USDOT), Bureau of Transportation Statistics (BTS), "Airline Origin and Destination Survey (DB1B)." http://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=125&DB_Name=Airline%20Origin%20and%20Destination%20Survey%20%28DB1B%29

U.S. General Accounting Office "Airline Competition: Higher Fares and Less Competition Continue at Concentrated Airports."1993.

APPENDIX

Table A1: U.S. Major Air Carriers and Their Hubs and Focus Cities*

Major Carriers	Hubs	Second Hubs	Focus Cities
American Airlines	DFW, ORD, MIA, STL, SJU	JFK, LGA	BOS, LAX, RDU
Alaska Airlines	SEA, ANC, PDX, LAX		SFO
Continental Airlines	IAH, EWR, CLE		
Delta Air Lines	ATL, SLC, CVG, JFK	LAX	MCO, LGA, BOS
Northwest Airlines	DTW, MSP, MEM		IND, HNL
United Airlines	ORD, DEN, IAD, SFO, LAX		
US Airways	CLT, PHL, PHX, LAS		DCA, LGA, PIT
America West	PHX, LAS, PHL, CLT	PIT	DCA, LGA, BOS
ATA Airlines	MDW		HNL,OAK
Horizon Air	SEA, PDX, LAX		DEN
Frontier Airlines	DEN		
Southwest Airlines			LAS, MDW, PHX, BWI, OAK, HOU, DAL,LAX, MCO, SAN
JetBlue Airways			JFK, BOS, FLL, OAK, IAD

***Lists of Airport Abbreviations and the Full Names**

Abbr.	Full Name
DFW	Dallas-Fort Worth International Airport
ORD	Chicago O'Hare International Airport
MIA	Miami International Airport
STL	Lambert-St. Louis International Airport
SJU	Luis Munoz Marin International Airport in Puerto Rico.
JFK	John F. Kennedy International Airport
LGA	LaGuardia Airport
BOS	Boston Logan International Airport
LAX	Los Angeles International Airport
RDU	Raleigh-Durham International Airport
SEA	Seattle-Tacoma International Airport
ANC	Ted Stevens Anchorage International Airport
PDX	Portland International Airport
SFO	San Francisco International Airport
IAH	Houston George Bush Intercontinental Airport
EWR	Newark Liberty International Airport
CLE	Cleveland Hopkins International Airport
ATL	Hartsfield-Jackson Atlanta International Airport
SLC	Salt Lake City International Airport
CVG	Cincinnati/Northern Kentucky International Airport
MCO	Orlando International Airport
DTW	Detroit Metropolitan Airport
MSP	Minneapolis-Saint Paul International Airport
MEM	Memphis International Airport
IND	Indianapolis International Airport
HNL	Honolulu International Airport
DEN	Denver International Airport
IAD	Washington Dulles International Airport
CLT	Charlotte Douglas International Airport
PHL	Philadelphia International Airport
PHX	Phoenix Sky Harbor International Airport
LAS	McCarran International Airport
DCA	Ronald Reagan Washington National Airport
PIT	Pittsburgh International Airport
MDW	Chicago Midway Airport
OAK	Oakland International Airport
BWI	Baltimore/Washington International Thurgood Marshall Airport
HOU	Houston George Bush Intercontinental Airport
DAL	Dallas Love Field Airport
MCO	Orlando International Airport
SAN	San Diego International Airport
FLL	Fort Lauderdale-Hollywood International Airport

Table A2: Comparison of GLIMM Regression Results in Different Scenarios (on Pooled, TCS, VCS or TVCS Routes)

Pooled Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
Parameter Est.	-1.04	3.07E-04	14.38	-1.70E-04	7.54E-04	2.09E-03	0.46	0.25	-0.05	-0.55	-1.28	-0.27	0.44	0.86	1.53	0.90
t Value	-6.01	3.3	16.36	-9.17	2.2	2.12	12.61	6.67	-1.43	-52.1	-11.2	-4.07	7.67	13.71	16.84	14.39
Odds Ratio	0.35	1.03[a]	4.21[b]	0.84[c]	1.08[d]	1.23[e]	1.58	1.28	0.95	0.58	0.28	0.76	1.55	2.35	4.60	2.47
-2 Residual log Pseudo-Likelihood			290149.5				Generalized Chi-Square/ DF			0.89						
TCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
Parameter Est.	-1.56	1.74E-04	**6.82**	-4.12E-05	-3.1E-04	8.00E-04	**0.14**	**0.13**	-0.08	-0.24	-0.60	**-0.06**	0.11	0.40	0.41	0.30
t Value	-7.83	1.53	**7.8**	-2.33	-0.92	0.65	**2.08**	**1.96**	-1.13	-13.6	-4.25	**-0.93**	1.88	6.56	4.74	4.52
Odds Ratio	0.21	1.02[a]	1.98[b]	0.96[c]	0.97[d]	1.08[e]	1.15	1.14	0.92	0.78	0.55	0.94	1.11	1.49	1.50	1.34
-2 Residual log Pseudo-Likelihood			119904.1				Generalized Chi-Square/ DF			0.93						
VCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
Parameter Est.	2.51	**-5.32E-05**	**1.11**	-1.21E-04	**-3.9E-03**	**-3.3E-03**	**0.60**	**0.17**	-0.01	-0.57	**0.06**	**-0.05**	**0.06**	**-0.07**	0.37	**0.06**
t Value	8.11	**-0.35**	**0.69**	-3.16	**-6.52**	**-2.1**	**7.86**	**2.14**	-0.07	-24.8	**0.43**	**-0.46**	**0.73**	**-0.63**	2.75	**0.59**
Odds Ratio	12.25	1.00[a]	1.12[b]	0.9999[c]	0.68[d]	0.72[e]	1.83	1.19	0.99	0.57	1.06	0.95	1.06	0.94	1.45	1.06
-2 Residual log Pseudo-Likelihood			86237.4				Generalized Chi-Square/ DF			0.76						
TVCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$OHUB_i$	$CHUB_i$	$DHUB_i$
Parameter Est.	-0.84	**7.35E-04**	**26.39**	-5.44E-05	**4.1E-03**	1.99E-03	**0.64**	**0.38**	-0.07	-0.78	-2.04	-0.59	**0.16**	1.01	1.63	1.05
t Value	-2.32	**4.49**	**14.58**	-1.14	**6.04**	1.14	**11.47**	**6.83**	-1.26	-45.8	-7.9	-4.54	**1.42**	8.53	7.86	8.9
Odds Ratio	0.43	1.08[a]	14.01[b]	0.95[c]	1.51[d]	1.22[e]	1.90	1.47	0.93	0.46	0.13	0.56	1.17	2.74	5.12	2.86
-2 Residual log Pseudo-Likelihood			83275.4				Generalized Chi-Square/ DF			0.87						

a. Odds ratio for a 100 unit increase in the booking frequencies;
b. Odds ratio for a 1/10 unit increase in the yield;
c. Odds ratio for a 1000 unit increase in the route HHI;
d. Odds ratio for a 1.0E+06 unit increase in the income;
e. Odds ratio for a 1.0E+10 unit increase in the population.

Table A3: Standardized Coefficients from GLIMM Regression in Different Scenarios (Pooled, TCS, VCS and TVCS Routes)

Pooled Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-1.95	24.35	92.13	-60.62	14.84	14.77	46.43	24.95	-5.50	-182.88	-78.07	-27.50	50.04	94.22	126.25	98.89
t Value	-70.93	3.3	16.36	-9.17	2.2	2.12	12.61	6.67	-1.43	-52.1	-11.2	-4.07	7.67	13.71	16.84	14.39
TCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-2.42	7.97	**29.19**	**-11.40**	-4.04	2.89	**9.01**	**8.47**	-5.09	**-51.58**	**-20.57**	-3.77	**7.59**	**26.40**	**21.59**	**18.79**
t Value	-88.36	1.53	**7.8**	**-2.33**	-0.92	0.65	**2.08**	**1.96**	-1.13	**-13.6**	**-4.25**	-0.93	**1.88**	**6.56**	**4.74**	**4.52**
VCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-2.56	-2.33	3.91	**-18.10**	**-40.32**	**-13.89**	**32.97**	**9.48**	-0.32	**-101.11**	2.34	-2.55	3.68	-3.88	**18.92**	3.39
t Value	60.18	-0.35	0.69	**-3.16**	**-6.52**	**-2.1**	**7.86**	**2.14**	-0.07	**-24.8**	0.43	-0.46	0.73	-0.63	**2.75**	0.59
TVCS Routes	*INT.*	$FLTS_{i,t-1}$	$YLD_{i,t-1}$	$RHHI_{i,t-1}$	$INCO_{it}$	POP_{it}	WIN_t	SPR_t	SUM_t	*TIME*	$SLOT_i$	$GATE_i$	VAC_i	$ORIHUB_i$	$CONHUB_i$	$DESTHUB_i$
Parameter Est.	-0.62	**32.37**	**79.11**	-7.15	**41.43**	8.54	**36.33**	**21.66**	-4.06	**-144.21**	**-57.02**	**-34.26**	10.18	**64.72**	**60.76**	**67.53**
t Value	-11.88	**4.49**	**14.58**	-1.14	**6.04**	1.14	**11.47**	**6.83**	-1.26	**-45.8**	**-7.9**	**-4.54**	1.42	**8.53**	**7.86**	**8.9**

Yan Du *is an assistant professor in the Division of Business and Management at Beijing Normal University–Hong Kong Baptist University United International College (UIC), located in Zhuhai China. She received her Ph.D. in economics from Oregon State University. Prior to joining UIC, Du worked as a senior strategic marketing analyst in the Forecasting Department at FedEX Corporate Services Inc., Memphis. She has conducted extensive research in airline economics and management, including pricing, strategic alliances, competition, customer relationship, and optimization problems.*

B. Starr McMullen *is professor emeritus of economics at Oregon State University. She is well known in the transportation community for her research and publications on various aspects of transportation economics, including topics such as competition, productivity, and costs in the airline, rail, and motor carrier industries, transportation infrastructure finance, and road user fees. McMullen is past president of both the Transportation and Public Utility Group (an American Economic Association affiliate group) and the Transportation Research Forum. She is past editor of* Research in Transportation Economics *and continues to serve on the editorial board of several journals in addition to the Economics Committee of the Transportation Research Board.*

Horizontal Cooperation in Network Expansion: An Empirical Evaluation of Gas Transportation Networks

by Rafay Ishfaq, Mark Clark, and Uzma Raja

This research presents a coordination approach for the expansion of gas transportation networks to serve an increasing customer base. An empirical study of natural gas markets in the southeastern United States shows that horizontal cooperation among transportation service providers (i.e., pipeline companies) allows for expanding the gas transportation networks efficiently to serve new customers. The benefits of coordination are identified through key structural elements such as number and location of additional pipeline links, lower infrastructure expansion costs, and demand segmentation for the gas transportation service providers.

INTRODUCTION

The significant increase in demand for natural gas in the U.S. industrial sector has renewed a strategic interest in gas transportation networks. The scope of gas supply chains and scale of logistics activities are expanding to ensure an efficient supply of gas to an increasing number of customers. There are a number of factors that contribute to the increase in demand, such as moderate prices of natural gas relative to coal, discovery of abundant sources of domestic (shale) natural gas, and higher operational efficiency of gas-based technologies. The increase in demand has encouraged major investments in developing gas production capacity in the United States. In 2011, 95% of the total natural gas consumed in the country was produced domestically (Barteau and Kota 2014).

One of the largest consumers of natural gas in the United States is the electric power industry. Not only because a majority of the new electric power generation units being installed in the United States are based on gas-fired technology, but many old coal-fired power plants are being converted to use natural gas (Lapides et al. 2011). The addition of new and retrofitted power plants has increased the demand for natural gas, which exceeded 9.1 trillion ft3 in 2012 (EIA 2013). The projected increase in the demand for natural gas has raised concerns about logistics and transportation capabilities of the existing gas distribution networks. Unlike other surface (road and rail) transportation modes, capacity in a distribution pipeline is already in use by existing customers. In this case, expanding transportation networks to connect additional customers to gas supply requires careful consideration and planning.

This study contributes to the academic literature by proposing an arrangement for network expansion based on the concept of horizontal cooperation among competitors. In this setting, gas pipeline companies, which otherwise compete with each other, cooperate to serve respective segments of the market through mutual agreement. In a situation where a sizeable new demand for natural gas would result in an aggressive competition among pipeline companies, a strategy based on cooperation may provide a better alternative that is beneficial for partnering firms as well as customers. The benefits of coordinated expansion of gas transportation networks are analyzed and discussed in relation to extant theory. To develop this understanding, the logic of industrial organization theory and concept of horizontal cooperation among competitors is used.

The paper shows that horizontal cooperation can yield lower expansion costs while providing equal business opportunity for participating firms. The dynamics of gas transportation are represented by a network model, which also incorporates the requirements for expanding transportation

infrastructure. This model includes relevant supply-demand requirements, network expansion costs, gas transmission capacity, and elements of gas pipeline infrastructure. Real-world data from gas pipelines in the southeastern United States are used in an empirical evaluation of the existing gas transportation networks to identify key strategic issues concerning collaborative network expansion. The scenario where different pipeline companies compete for gas supply business in a new market is compared with another scenario driven by the horizontal cooperation approach. The results provide empirical evidence that cooperation not only results in an efficient expansion of the pipeline network to support the needs of new customers (power plants) but also provides equal opportunities for partners firms (gas transportation service providers) in the new market.

BACKGROUND

In the past, a major concern about adequate sources of gas supply existed due to the limited domestic natural gas reserves. As late as 2007, the United States was expected to be increasingly dependent on imports due to the constrained domestic supply. As new technologies of horizontal drilling and hydraulic fracturing have increased domestic gas production, reliance on gas imports is no longer a major issue (Mouawad 2009; Yergin and Ineson 2009). According to the 2012 Annual Energy Outlook Report of the U.S. Department of Energy (EIA 2012), domestic shale gas supply is expected to increase from 10% of total gas production in 2010 to 49% by 2035, thus making domestic production of natural gas greater than the expected national demand. The domestic production capacity is estimated to satisfy demand for gas from large industrial users in the electric power generation industry (Paltsev et al. 2011).

The other key issue, which is relevant in this context, is the impact of federal environmental regulations. The electric power plants built in the U.S. had primarily used coal as a fuel in the combustion process to produce high pressure steam. Burning coal in this process releases greenhouse gases, which are harmful to the environment. To control the emission of greenhouse gases, the U.S. Congress passed new amendments to the 1963 Clean Air Act, which became effective January 1, 2012. These regulations limit the hazardous air pollutants emitted by coal-fired electric power plants (EIA 2012). The electric power companies are required to bring these coal-fired power plants into regulatory compliance or face significant monetary penalties. One of the options available to power companies is installing scrubbers, which capture sulphur oxides from coal combustion and filter them into disposable matter. However, this additional step in power generation adds a significant capital and operating expense for power companies, affecting the cost per unit ($/kilowatt-hour) of generated electricity. The lower efficiency and higher maintenance costs of old coal-fired power plants do not offer an economical case for recovering capital investments in the environmental retrofits (Shahidehpour et al. 2005). For these operational and financial reasons, power companies opted to replace coal-fired power plants with gas-fired technology, instead of installing environmental controls on the old coal-fired power plants (Lapides et al. 2011). The new power plants are typically built on the same sites as old coal-fired plants. The current sites are already connected to the national electric grid; they already have necessary approvals and permits for locating a power plant and the necessary human and infrastructure resources are in place.

The legislation enacted by the U.S. Congress, such as the Natural Gas Policy Act (1978) and Natural Gas Wellhead Decontrol Act (1989), deregulated the natural gas industry. Issued in 1992, U.S. Federal Energy Regulatory Commission (FERC) Order No. 636 states that "pipelines must separate their transportation and sales services, so that all pipeline customers have a choice in selecting their gas sales, transportation, and storage services from any natural gas provider, in any quantity." These legislative actions resulted in a competitive marketplace in which different players engage in the sales and purchase of transportation, storage, and distribution of natural gas.

The transportation of natural gas from a gas wellhead to the customer involves multiple organizations. The natural gas supply chain starts at its upstream end with gas production. The

uniqueness of the natural gas supply chain is that it consists of a single product. All production sources are required to process the gas extracted from underground sources to meet the quality standards of natural gas. The output of natural gas wells is collected through a network of gathering pipes which deliver natural gas (with its impurities) to processing plants. These gas processing plants bring natural gas to the required national quality standards.

The other key player in the gas supply chain is gas storage companies. These companies operate underground storage facilities (such as aquifers, caverns, and old gas wells) where natural gas can be stored. The gas is injected under pressure into these storage areas and later extracted, as needed. Storage facilities help absorb demand fluctuations during the year. A significant aspect of the storage facilities is these are natural underground areas that are very expensive to duplicate above the ground. Thus, from a supply chain design perspective, storage locations and capacity are usually fixed.

The gas supplied by producers is purchased by gas distributors and marketing companies. The distributors are typically gas utilities which service customers in large cities and municipalities. Natural gas is delivered to city gates by pipeline companies from where a distribution company takes over and transports the gas to residential and commercial customers. Large industrial customers such as electric power plants typically buy gas directly from the gas pipeline companies and gas marketers due to higher end-of-line pressure requirements. The available supply of natural gas is also bought and sold through the marketing companies. Marketers provide coordination services such as purchase, storage, transportation, and all intermediate steps required to facilitate the sale and delivery of natural gas. A key service offered by marketing companies is managing the transportation arrangements between different pipelines. When natural gas in one pipeline is to be delivered to a customer located on another pipeline, gas transportation hub operators are instructed by the marketing companies to make pressure adjustments to transfer gas through these pipelines.

To study the effects of an increase in gas demand from new power plants, a strategic review of the natural gas transportation networks is required at the national level. Such a review would make recommendations for installing new capacity on existing lines and/or building new interstate pipelines. However, an evaluation at such a level involves many players and stake holders, increasing the scope of work, which is beyond the focus of this study. This paper is focused on a regional context and transportation/supply considerations for distribution pipeline firms. The empirical evaluation presented in this paper is focused on issues related to connecting new users (power plants) of natural gas to existing pipelines (under current capacity restrictions) and identifies the benefits of coordination in expanding gas transportation networks.

HORIZONTAL COOPERATION IN GAS TRANSPORTATION NETWORKS

The gas transportation network in the U.S. comprises more than 210 natural gas pipeline systems (EIA 2013). The 30 largest interstate pipelines transport about 80% of the total gas supply (EIA 2013). In the gas transportation industry, new capacity is added only when there are new customers in the market, such as the electric power industry where many power plants are undergoing a change in fuel from coal to natural gas. These developments in the electric power industry have presented a significant business opportunity for pipeline companies to expand their revenue base.

Industrial organization theory in the field of strategic management describes the dependency that exists among competitor firms that leads to the formation of strategic groups (Harrigan 1985). The concept of strategic groups serves as a foundation for the idea proposed by Sollner and Rese (2001) in which firms that would otherwise compete with each other mutually agree to each serve a different segment of the market. In this context, firms may elect to serve narrowly defined customers (based on some criterion, such as cost-to-serve) and thereby not compete head-on with their competitors in the same market. A strategic group may include many firms or just one member (single pipeline company), with each firm following its individual strategy (Audy et al. 2012; Sollner and Rese

2001). Formation of such groups protects its members from invasion by other competitors due to their relative cost position, among other factors (Caves and Porter 1977).

The concept of strategic groups can also be examined through a network of relationships among competitors (Zaheer et al. 2000). Bengtsson and Kock (1999) classified the nature of relationships among competitors into four different types, based on the continuum between cooperation and competition: coexistence (social and information exchange among partners, no economic exchange), cooperation (business, information, and social exchange), co-opetition (partners cooperate in some ways and compete in others) and competition (a zero sum arrangement). According to this classification, competitors can coexist in a market by keeping their distance and avoiding interaction. When competing firms do interact, they try to reduce conflicts through cooperation. This situation arises when competitors have common goals (e.g., when pipeline companies decide to cooperate in facilitating gas connectivity to power plants to promote use of natural gas in electric power generation). The cooperation among competitors does not necessarily mean they do not compete with each other. Under co-opetition, competitors can cooperate in one market, such as power generation market, and compete in others, such as industrial and residential markets (Bengtsson and Kock 2000). In this paper, our focus is on cooperation among firms (pipeline companies), which operate at the same level in the gas supply chain, referred to as horizontal cooperation (Cruijssen et al. 2007b). Through close cooperation and joint planning, partner pipeline companies can increase the competitiveness of their gas transportation networks (Vanovermeire et al. 2013).

The existing literature in the area of horizontal cooperation in logistics has focused on issues related to pooling of transportation resources, leveraging specific strengths and capabilities of the other participating firms, trading of complementary resources to achieve mutual gains, and to eliminate the high cost of duplication (Schmoltzi and Wallenburg 2011; Vanovermeire et al. 2013). Empirical research has indicated that horizontal cooperation can result in decreased cost, improved service, and protection of market position (Cruijssen et al. 2007c). According to Vos et al. (2002) synergies from cooperation among competitors can be achieved by restructuring transportation networks collectively by all partners. This approach was shown to yield benefits for all participant firms in the German consumer goods industry (Bahrami 2002). Cruijssen et al. (2007a) provided empirical evidence that horizontal cooperation provides cost savings for logistics service providers through joint planning of transportation routes.

Horizontal cooperation uses market segmentation based on two characteristics: how well market needs align with the capabilities of individual partner firms, and that each market segment offers an equal business opportunity to partner firms (Krajewska et al. 2007; Audy et al. 2010; Vanovermeire et al. 2013). The gains resulting from horizontal cooperation are measured in the form of cost savings (through increased efficiency, economies-of scale, and joint purchase power) and revenue opportunities. In the context of this research, pipeline companies may jointly coordinate market segmentation to identify a group of customers to be served by each partner firm, based on network expansion costs. Such a cooperative arrangement should provide equal opportunity to all participants for generating revenue. The feasibility of such an arrangement is supported by the limited transportation capacity of gas pipelines, which does not allow pipeline firms to compete in all markets and serve all customers.

In the next section, a model is presented that represents the gas transportation networks through various structural elements such as footprint of existing pipelines, routing options for expanding the network, demand and supply requirements, and optimal routes for installing new pipes.

NETWORK MODEL OF GAS TRANSPORTATION

A gas transportation network can be represented by a model using a graph composed of a collection of nodes and links. The footprint of a pipeline is identified by links which pass through different nodes. The nodes represent geographical locations and facilities (demand points and branching stations).

Additional requirements, such as transportation capacity, demand and supply requirements, and routing restrictions, can be added to the network model. The output of the model identifies optimal routing for installing new pipes and pressure stations, so that new demand nodes can be connected to supply nodes through the existing pipelines.

Earlier research has shown that optimal network configuration of gas pipelines has a tree-like structure (Rothfarb et al. 1970; Bhaskaran and Salzborn 1979). Thus, the minimum spanning tree approach provides a good basis for a mathematical model of gas transportation networks (Kawatra and Bricker 2000). The network model used in this paper follows this approach with updates to implement the network expansion requirements specific to the case studied here. The model is used to study different strategic issues related to pipeline expansion, i.e., which existing gas pipeline is most suitable to supply natural gas to the electric power plants, routing of pipes for the new pipelines, consideration for available gas capacity, and the location/size of new gas pressure regulation stations.

Unlike freight transportation and telecommunication networks, a design of gas pipeline networks has to consider additional issues such as gas pressures, flow rates, and pressure regulation (Martin et al. 2006). The literature on pipeline networks is generally focused on optimizing the routing of pipeline networks, selecting diameter of the pipes (related to transmission capacity), and location of pressure regulation stations (Zheng et al. 2010; Kabirian and Hemmati 2007). For expanding an existing gas pipeline network, a major area of interest is in selecting the segments of pipeline where reinforcements are added to satisfy increasing demand (Babonneau et al. 2012; Andre et al. 2009).

Due to long distances between the gas-wells and demand points, pressure regulation stations are widely used in transporting natural gas. The gas regulation stations provide pressure differential across a pipe to control the flow of gas. The pressure regulation is modeled in the form of inlet and outlet pressures on each arc in a network graph (Rios-Mercado et al. 2002). The inlet and outlet pressures across an arc determine the direction of gas flow.

Modeling Framework

The network model used in this paper is based on a grid-based graph that represents a geographical region, in terms of nodes and links. The grid is useful in identifying population centers, environmentally protected land, and other right-of-way areas through which pipelines cannot pass. Such no-go areas are identified by disconnecting the corresponding nodes from the other nodes in the graph. The nodes in the graph are represented by N, which consists of nodes through which existing pipelines pass (represented by set P), nodes to represent the locations of power plants (set K), and nodes through which new pipes can be routed (set R). The node set P is further partitioned into subsets, represented by P_g, where each subset of nodes corresponds to different pipelines (indexed by g). The connectivity within P_g is implemented by setting c_{ij}=0, for nodes i and j that are inter-connected. Otherwise, c_{ij} represents the unit cost of installing a new link between nodes i and j. Each pipeline node (indexed by l) in subset Pg is characterized by its gas pressure (pounds per square inch), denoted by π_l. The gas flow supply (ft^3/day) available in a pipeline g is represented by κ_g. This parameter can be used to include additional gas supply in the future, as more shale gas fields are added to the supply network. The supply of natural gas to a power plant is needed at a specific pressure π_k under the condition $\pi_k < \pi_l$. In order to meet these gas pressure requirements, pressure regulation may be needed. A pressure regulation station can be installed at a unit cost of γ per psi of gas pressure.

The supply of natural gas to a power plant requires laying new pipes. The model finds the lowest cost path by routing new pipes through available nodes to one of the existing gas pipelines. The demand-supply matrix D provides the details about the sources (gas pipelines) and demand (power plants) of gas supply. An element dik of matrixD of the supply-demand matrix represents a demand node (power plant) by -1, supply node (gas pipeline) by +1, and connector node by 0. Note

that for each power plant, there may be multiple sources of supply (pipelines). Hence each column of the demand-supply matrix will have a single -1 entry and multiple +1 entries.

There are three types of decision variables in the model. The decision variables X_{ij}^k represent the binary choice of using link (i,j) for routing the new pipeline to supply natural gas to power plant k. Note that for two different power plants k and m, X_{ij}^k and X_{ij}^m variables may use the same link (i,j), especially if k and m are to be connected on the same branch of the new pipeline. To properly identify all the links on which new pipes will be installed, binary decision variables Y_{ij} are used. These variables properly identify the links on which new pipelines will be constructed, based on the X_{ij}^k variables. The decision variables P_l represent the difference in gas pressure between what is currently available at a gas pipeline node l and the pressure that is needed at the end-of-line power plant(s). If there is a pressure differential, additional pressure regulation capacity may need to be installed on the pipeline.

Sets:

G = Existing gas pipelines; {1, 2 ... g}
P_g = Nodes associated with gas pipeline g
K = Nodes where new gas-fired electric power plants k are located
R = Available nodes for new pipelines,
N = Set of nodes
E = Set of links

Parameters:

c_{ij} = Cost of installing new gas pipeline on link (i,j)
γ = Cost to add unit pressure regulation (psi) at a gas pipeline node
d_{ik} = Natural gas supply-demand matrix
κ_g = Flow capacity of pipeline g
α_k = Gas requirement at power plant
π_l = Available gas pressure at pipeline node l
π_k = Gas pressure requirements at power plant k
M = Large number

Decision Variables:

X_{ij}^k = 1, if link (i,j) is needed to supply gas to plant k; 0 otherwise
Y_{ij} = 1, if gas pipeline is constructed over link (i,j); 0 otherwise
P_l = Pressure differential (psi) required at pipeline node l

Model Formulation:

(1) $$(\boldsymbol{P}) \quad \min_{(i,j)\in E} c_{ij} Y_{ij} + \sum_{l \in P} \gamma\, P_l$$

Subject to:

(2) $$\sum_{(i,j)\in E} X_{ij}^k - \sum_{(i,j)\in E} X_{ji}^k \quad \leq \quad d_{ik} \qquad ; \forall\, k \in K, i \in N$$

(3) $$\sum_{k\in K} X_{ij}^k \quad \leq \quad M\, Y_{ij} \qquad ; \forall\, (i,j) \in E$$

(4) $$\sum_{k\in K, i\in P_g, j\in P_{q\neq g}} X_{ij}^k \quad = \quad 0 \qquad ; \forall\, g \in G$$

$$(5) \quad \sum_{k \in K, i \in P_g, j \in R \cup K} \alpha_k \; X_{ij}^k \quad \leq \quad \kappa_g \qquad ; \forall \, g \in G$$

$$(6) \quad \sum_{j \in R \cup K} (\pi_l - \pi_k) \; X_{ij}^k \quad \leq \quad P_l \qquad ; \forall \, l \in P, k \in K, \pi_l \geq \pi_k$$

$$X_{ij}^k, Y_{ij} \in \{0,1\}; \; P_l \geq 0 \qquad ; \forall \, (i,j) \in E, k \in K, l \in P$$

The objective function (1) represents the total expansion cost of the transportation network. The first term of the objective function deals with the total cost of installing new gas pipelines. The total cost of adding new or updating existing pressure regulation stations at pipeline node *l* is given by the second term, using decision variables P_l. The objective function is minimized over a number of constraints. Constraint (2) is used to find the lowest cost path from each power plant to one of the available pipelines for gas supply. For a given index *i* in constraint 2, index *j* in the two summations, is from two different instances of set E. Hence, node *j* marks the end of one link as well as the start of another link. These constraints consider multiple root-nodes where demand for plant *k* can be serviced. These root-nodes correspond to different supply pipelines. The links (pipes) are installed to service a power plant based on the smallest branch length to a root-node. If needed, multiple power plants can be connected together through tree-like paths. Constraint (3) is used to identify the links where new pipeline(s) will be constructed. A new pipeline cannot be installed to bridge (connect) two or more existing pipelines, as represented by constraint (4). Constraint (5) ensures that demand of natural gas from the newly constructed/retrofitted power plants to an existing pipeline does not exceed its available supply. In order to meet the gas pressure requirements of the power plants connected to the new pipelines, pressure in the supply pipelines may have to be adjusted. Constraint (6) determines the difference between available gas pressure (at different supply pipeline nodes) and gas pressure requirements at all the power plants connected to supply pipeline node *l*. The requirements of pressure regulation are determined by the largest pressure differential among all supply and demand points on a branch. Note that there may be some adjustments of gas pressure needed at delivery points for specific customers. However, in a model focused on network-level considerations, local operational details are not included.

The output of the model provides optimal routing of new pipes, which connect the demand points (power plants) to the most suitable supply point (gas pipeline) such that expansion costs of the new pipes and pressure stations are reduced while considering demand requirements and supply restrictions. This model is used to evaluate the differences between the uncoordinated and coordinated approaches for expanding the gas transportation networks. The differences are measured in terms of the expansion costs, which are based on routings of new pipes, supply and demand points in the network, and installation of pipes and pressure stations. The benefits of horizontal cooperation in network expansion are explored through a study of gas pipelines and power plants in the southeastern U.S. region.

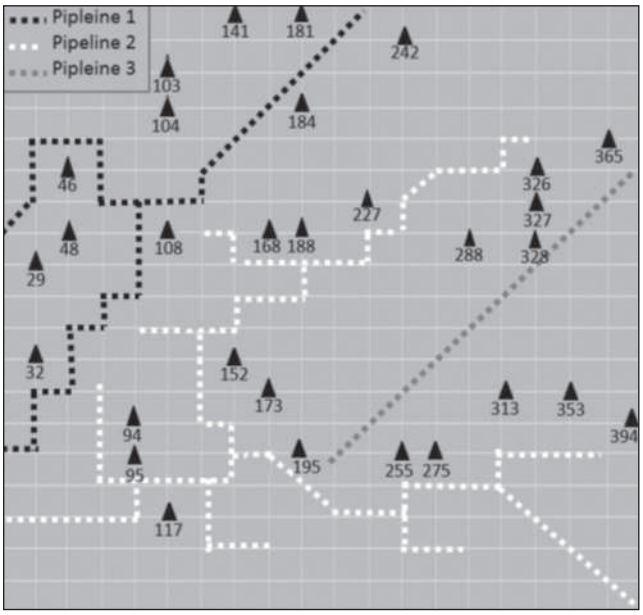
SOUTHEASTERN U.S. GAS PIPELINE ENTWORK

This section presents a study to analyze key issues related to pipeline expansion in order to serve the demand from the new gas-fired power plants in the southeastern United States. The study considers three major interstate pipelines in the region; Southern Natural Gas, Transco, and Kinder Morgan. Kinder Morgan pipeline originates from three locations in southern Louisiana and southern Texas, converging around Nashville, TN. From there the pipelines travel through Kentucky and then on through Ohio to Boston and New York. Southern Natural consists of two main lines through the southeast region, one of which originates in southern Louisiana and the other originating in northern Louisiana. Both lines pass through Mississippi and Alabama, and terminate in Georgia. Transco is the third major pipeline that runs through the southeast region. It originates in southern Texas and

terminates in the State of New York, passing through Georgia, South Carolina, and North Carolina, before reaching New York. These pipelines are identified in Figure 1 as Pipeline 1 (Kinder Morgan), Pipeline 2 (Southern Natural), and Pipeline 3 (Transco).

The geographical area of this study is represented by a graph (Figure 1), which comprises 400 nodes on a 20x20 grid where vertical (horizontal) distance between two nodes represents 50 miles (diagonal distance is 70 miles), covering a total area of one million square miles. The study includes 30 nodes, which represent new gas-fired power plants, and 103 nodes, which represent the existing gas pipelines. The power plant and pipeline nodes are inter-connected through a set of 1,484 horizontal, vertical, and diagonal arcs. These arcs are used to route new pipes from existing gas pipelines to new gas-fired power plants.

Figure 1: Gas Pipelines and Power Plants



The coal-fired power plants included in this study operate in Alabama, Georgia, Tennessee, Kentucky, South Carolina, and North Carolina, each with a power generation capacity larger than 600MW. There are 30 such plants in these six states with an average size of 1,581 MW. The smallest is 601 MW and the largest plant is 3,564 MW. The data on each power plant (location, year built, power generation capacity, current financial liabilities, and carbon costs) were extracted from the U.S. Energy Information Administration (EIA) and industry databases related to the energy industry (Table 1). In Figure 1, power plants are identified by their ID in Table 1.

The cost of installing a new gas pipeline link is set at $1 million per mile (INGA 2009). The demand for natural gas at the electric power plant is calculated using the estimates provided by EIA, i.e., 0.00789 MCF of gas is used per KWh of generated electrical energy (EIA 2013). The supply nodes (gas pipelines) can provide gas pressures that range between 900 psi and 1100 psi, while the pressure requirements at the power plants range between 400 psi and 600 psi (Kabirian and Hemmati 2007). The data about gas supply capacity in the three pipelines were obtained from the respective gas companies: P1 – 106 MMCF/day, P2 – 25,000 MMCF/day, and P3 – 25,000 MMCF/day.

Table 1: Power Plants

Plant ID	Location (State)	Plant Name	Generation Capacity (MW)	Natural Gas Demand (MMCF)	Natural Gas Pressure (psi)
32	AL	Colbert	1250	342	579
94	AL	Gorgas	1417	387	558
95	AL	Miller	2822	771	644
117	AL	Gaston	2013	550	652
152	GA	Hammond	953	260	520
173	GA	Bowen	3499	956	662
195	GA	Yates	1487	406	553
255	GA	Scherer	3564	974	523
275	GA	Harllee Branch	1746	477	647
46	KY	Paradise	2558	699	571
103	KY	Cane Run	654	179	571
104	KY	Mill Creek	1717	469	604
141	KY	Ghent	2226	608	592
181	KY	H L Spurlock	1279	350	503
184	KY	E.W.Brown	739	202	623
242	KY	Big Sandy	1233	337	669
288	NC	Cliffside	780	213	477
326	NC	Marshall	1996	546	630
327	NC	Riverbend	601	164	566
328	NC	GG Allen	1155	316	621
365	NC	Belews Creek	2160	590	625
313	SC	Urquhart	650	178	469
353	SC	Wateree	685	187	505
394	SC	Williams	633	173	588
29	TN	Johnsonville	1485	406	580
48	TN	Cumberland	2600	711	502
108	TN	Gallatin	1255	343	652
168	TN	Kingston	1700	465	669
188	TN	Bull Run	950	260	472
227	TN	John Sevier	800	219	494

RESULTS AND ANALYSIS

To study the effect of coordination in expanding gas transportation networks, model (P) was used with data in two main scenarios. In the first scenario, a coordinated expansion of gas transportation networks was undertaken to identify a pipeline (among all candidate pipelines) which will serve a specific power plant. Since expansion of a pipeline network represents a significant portion of the cost of developing the capability to serve customers, it follows that a successful firm would be the

one that can serve customers with lowest network expansion costs. We use this setting to select which pipeline will service a specific power plant based on the lowest total transportation network expansion costs. The second scenario is based on connecting power plants to the network of each pipeline company, separately. This setting corresponds to the uncoordinated expansion of the gas transportation network. Note: A pipeline firm may choose to serve all or a part of the market. Our intent in using the two alternative scenarios is for the purpose of comparison.

The model and corresponding data was coded into AMPL, which integrates a modeling language for describing optimization data, variables, objectives, and constraints (Fourer, Gay and Kernighan 2002). The model was solved to optimality using CPLEX 12.4 solver for linear mathematical programming models. The outputs of the model from both scenarios were compiled to provide information about: (i) which pipeline is most suitable for supplying natural gas to power plants based on the pipe installation costs and available gas supply, (ii) number and location of new branches added to the existing pipelines, (iii) new pipe links installed, and (iv) power plants allocated to each supply pipeline for service. The outputs of these scenarios were compared using key structural elements such as number and location of new links, expansion costs, and the allocation of power plants to gas pipelines for service. The best option is characterized as one that adds the least number of new branches with fewest pipes added to the network, and one that will need the smallest pressure differential between supply pipelines and power plants. These choices lead to a least cost expansion of the gas transportation network.

The solution of the model in AMPL identifies the links that are used for installing gas pipes to service each power plant. These links were identified by the start and end nodes (indexed by i and j in the model). This information was recorded for each pipeline and power plant in the case study. For each pipeline, the number and location of pressure regulation stations were also recorded. The scale used in the grid to represent the network graph was used to calculate the length of new pipe links. These detailed outputs were compiled into summary tables, which are discussed below.

The summary output of the first scenario is presented in Tables 2 and 3. The results show that in a coordinated expansion of the gas transportation network, each pipeline serviced a similar proportion of natural gas demand in the case study, e.g., pipelines P1 and P3 serviced 31% and 26% of the total gas demand, respectively (see last column in Table 2). Thirty-three percent of the power plants were connected through pipeline P1, 40% were connected through P2, and 27% were connected through pipeline P3. The significance of this result is related to the concern that by participating in collaborative planning, pipeline companies lose the opportunity to capture market share and that some participants will be at a disadvantage in this arrangement. As the results show that for the southeastern region, the footprint of pipeline networks and the geographical dispersion of customers (power plants) allow participant pipeline companies to share a similar proportion of business opportunities in the new market.

Table 2: Pipeline - Power Plant Allocations

Plant Name (ID)	Location	Plant Name (ID)	Location	Plant Name (ID)	Location
Colbert (32)	AL	Gorgas	AL	Yates	GA
Paradise (46)	KY	Miller	AL	Harllee Branch	GA
Cane Run (103)	KY	Gaston	AL	Cliffside	NC
Mill Creek (104)	KY	Hammond	GA	GG Allen	NC
Ghent (141)	KY	Bowen	GA	Belews Creek	NC
H L Spurlock (181)	KY	Scherer	GA	Urquhart	SC
E.W.Brown (184)	KY	Marshall	NC	Wateree	SC
Big Sandy (242)	KY	Riverbend	NC	Williams	SC
Johnsonville (29)	TN	Gallatin	TN		
Cumberland (48)	TN	Kingston	TN		
		Bull Run	TN		
		John Sevier	TN		

Additional outputs of this scenario are shown in Table 3. The analysis shows that network expansion (and related costs) for each pipeline depends on its existing footprint. While pipelines P1 and P3 served new customers with about the same total natural gas demand (i.e., 31% and 26%, respectively), each pipeline's costs for installing new pipes was different. Pipeline P1 added 16 new links with a total length of 920 miles. Whereas, for a similar number of customers and gas demand, pipeline P3 needed 28 new links (75% more links that P1) for a total length of 1,520 miles. For pipeline P1, this level of expansion accounts for a significant increase (about double the length) compared with 630 miles of existing pipeline in the area (Kinder Morgan 2014).

Table 3: Summary Statistics of Expanded Pipeline Network

Pipelines	Plants Served	New Pressure Stations	New Links	Length of New Pipes	Gas Demand Serviced (MMCF)
P1	33%	8	16	920 mi	31%
P2	40%	8	18	980 mi	43%
P3	27%	2	28	1520 mi	26%

These results identify a potential shortfall for pipeline companies which view the network expansion decision myopically. The potential to capture a large share of the market is tempting until the reality of cost-to-serve is considered in the analysis. These results show that for some pipeline companies, the cost of expanding their current pipeline network may come at a prohibitively high cost. Conversely, a pipeline may have a footprint in a region that allows it to efficiently expand its services to new customers. Such is the case with the pipeline network of Southern Natural (Pipeline P2), which has an existing network footprint in the region that is well-suited for providing access to the power plants within the region. The pipeline P2 is allocated 40% of all the new customers in the study (most among all the pipelines), which account for 43% of all the demand from the new gas-fired power plants. These power plants are connected through 18 new pipe links (29% of all new links installed) with eight pressure regulation stations (same as pipeline P1). The total length of new pipes added to pipeline P2 (980 miles, see Table 3) accounts for a 29.8% increase to the existing

3,300 miles length of pipeline P2 in the region. This is the smallest percentage increase for a pipeline in the case study, and yet it covers the largest proportion (43%) of new demand.

Next, network model (P) is used in the uncoordinated case. Recall that in this setting, each pipeline company is considered individually to satisfy the demand from all power plants. The network model in this scenario identifies the optimal expansion of each pipeline's network, exclusively. The output of the model identifies the layout and routing of the new pipes in the expanded network of each pipeline. The output of the model for each pipeline is shown in Table 4. Note that for comparison, output of the previous scenario (coordinated expansion) is listed as base case.

Table 4: Comparison of Pipeline Networks

	Base Case	**Case: P1**	**Case: P2**	**Case: P3**
Network Expansion Costs ($M)				
Pipe Installation	2,060	3,960	3,710	4,910
Pressure Regulation	549	363	419	237
Total	2,609	4,323	4,129	5,147
Number of new branches	15	8	13	4
Plants serviced per branch (Avg.)	1.75	4.14	2.15	7.5
Number of new links	41	66	59	81
Length of new pipes (miles)	3,420	3,960	3,310	4,610

In the case of pipeline P1, all customers were connected by adding 66 new links (61% more links than base case). The new branches added to the original pipelines connect through eight locations, where half of these locations were different from the base case. The number of power plants serviced on each branch averaged 4.14, which is almost 2.5 times higher than the base case. This shows that pipeline P1's network requires a lot more dense expansion than the base case. The costs of installing new pipes on pipeline P1 were very high (92.2% compared with base case). In the case of pipeline P2, only two of the branch locations were common with the base case. Compared with pipeline P1, P2 used a higher number of branches (62% more) and a smaller number of power plants serviced by each branch. While the average number of plants on a branch (Avg. = 2.15) was still higher than the base case, pipeline P2 needed (44%) more pipe links to provide access to its customers. This caused the expansion costs of pipeline P2 to be much higher than the base case.

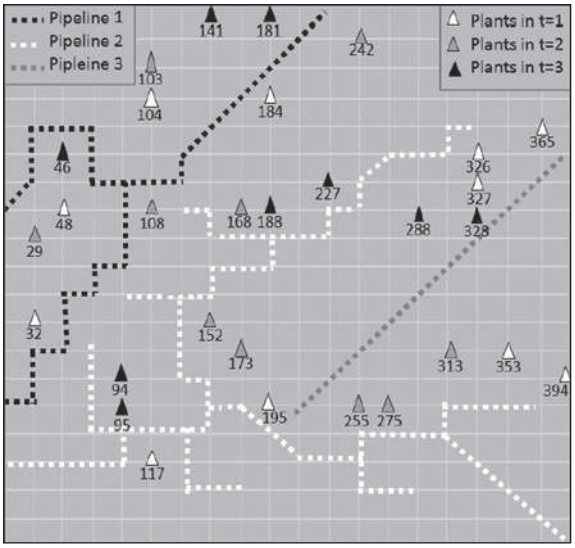
These results show that in expanding a pipeline network with an extensive footprint (such as pipeline P2), power plants were connected separately on a branch from the supply pipeline. When the pipeline network is not as extensive (as in the case of Pipeline P1), multiple power plants were connected together for service within a single branch. This observation was verified in the case of pipeline P3 (see Table 4). The data provided by the pipeline companies for this case study show that pipeline P3 has the sparsest network in the southeastern region. The result of the scenario identified that 81 new pipe links will be needed to connect all customers (power plants), which would add 4,610 miles to the existing network. The total expansion cost in the case of pipeline P3 was the highest among all the pipelines. However, there were only four new branches used by P3 to service power plants, with an average of 7.5 power plants served per branch. This is the highest number of power plants per branch among all the pipelines, increasing the utilization of the newly installed pipes.

The analysis presented above is based on the evaluation of gas pipeline networks to provide connectivity and service demand of all power plants. In this context, the results of the study has identified collaborative planning as the best approach toward expanding gas transportation networks. However, the power plants in question may have their own dynamics in terms of when a

power plant may decide to switch fuel and its demand of natural gas becomes active. This situation introduces a time-based dimension to the pipeline expansion decisions. In this situation, the benefits of coordinated network expansion may be affected. For the purpose of this study, the timed-demand of natural gas for the coal-fired power plants in the region was evaluated based on the operational, financial, and environmental credentials of each power plant. This evaluation is made to identify the time when demand for natural gas at each power plant will be active. Note that this is an experimental evaluation, as the timing information about when demand of gas for a power plant will be active is not publicly available.

For this part of the study, three time periods were considered (each period was set equal to four years, which is similar to the time frame involved in replacing an existing power plant and building a gas pipeline). The timed-demand of each power plant is determined by considering the fixed (capital) and variable (operational) costs. The fixed costs included in the evaluation are replacement cost of a new gas-fired plant and a power plant's current financial liabilities. The replacement costs are assumed to increases in each future time period at the rate of 10% annually, and the financial liabilities decrease at the same rate in the future time periods. The variable costs considered in the evaluation are fuel costs (coal and natural gas) and carbon emission costs. The data and information related to this evaluation were obtained from power company websites, energy council reports, and government agencies such as EIA and Environmental Protection Agency (EPA). To identify the time when gas demand of each power plant may become active, total costs were computed for the following four options: (a) coal-fired plant is replaced in t=1, (b) replaced in t=2, (c) replaced in t=3, and (d) fuel in the plant is not replaced. For each of these options, fixed and variable costs were used to calculate the total costs of each option. Based on these calculations, a time period is identified when switching fuel will result in the lowest total cost over the entire planning horizon. The result of this evaluation is shown in Figure 2. Each power plant is color coded (white, grey, and black) to identify the time period when its time-demand is activated. Note that while this evaluation is experimental and actual timed-demand may have a different pattern, this setting allows us to investigate the effect of timed-demand on the benefits of using the coordinated network expansion approach.

Figure 2: Timing of Natural Gas Demand



The network model was used to obtain optimal (expanded) network structure in each planning period separately. In each case (time period), pipelines that provide the lowest cost connection to the demand-active power plants were selected. This selection was made while evaluating all candidate pipelines, similar to the approach used in the previously considered coordinated expansion scenario. The output from the timed-demand case is compared with the case of coordinated expansion (referred to as the base case) in Table 5. This comparison showed that demand timing adversely affected the total expansion costs. The results show that by spreading demand across different time periods, more branches were installed to provide access to power plants. This setting did not offer the same economies of scale as were realized in the case of pooled demand. A branch installed for servicing customers in a specific time period had no capacity left over for customers that may need supply beyond the time frame when a pipeline was extended. This limitation resulted in using

more branches and installing additional pipes compared to the previously studied, coordinated expansion case of pooled demand. It is interesting to note that in the timed-demand case, market share of the pipeline companies did not change. Each company still held about the same power plant assignments, as shown previously in Table 2. These results show that network expansion costs will generally increase when power plants selectively switch fuel and activate their gas demand. To avoid this shortfall, it is worthwhile for the gas pipeline industry to engage major power companies in the decisions related to fuel-switch and the corresponding expansion of gas transportation networks. This collaboration will help all parties to develop a plan that can yield dividends in the form of lower expansion costs, which result from pooling demand.

Table 5: Effect of Timed Demand

	Timed Demand Case	Base Case
Network Expansion Costs ($M)}		
Pipe Installation	2,310	2,060
Pressure Regulation	821	549
Total:	3,132	2,609
Power Plants serviced by:		
Pipeline P1	10	10
Pipeline P2	11	12
Pipeline P3	9	8
Number of branches added:		
Pipeline P1	8	6
Pipeline P2	8	7
Pipeline P3	3	2

CONCLUSIONS

This paper highlights recent developments in the natural gas and related industries, which have renewed a strategic interest in gas transportation networks. The case of the electric power industry, one of the largest users of natural gas, is discussed. The prevalence of gas-fired technology in the electric power plants currently being built and switching of fuel to natural gas in coal-fired power plants have created a significant opportunity of revenue growth for pipeline companies. This paper presented a collaborative approach, based on the concepts of horizontal cooperation and strategic groups, which provides a system-level view of these opportunities for the competing pipeline companies.

The results of the study demonstrated that cooperation among pipeline companies provides mutual benefits for partnering firms and allows for better revenue opportunities through competitor-oriented market segmentation. The market segmentation was based on a cost-to-serve criterion. This approach allocates customer demand to a pipeline, which can provide access to natural gas with the least network expansion costs. The coordinated approach not only assured an equal opportunity for participant firms in the study, it also resulted in an efficient gas distribution network.

The paper also discussed the uniqueness of gas transportation networks compared to other modes of surface transportation. The supply-demand requirements, network expansion costs, transmission capacity, and elements of gas pipeline infrastructure were represented in a network model. The study presented in this paper identified key structural elements such as number and location of new links, expansion costs, and the allocation of power plants to gas pipelines for service. The results showed that for a pipeline company, cost-to-serve new customers depend on the footprint of its existing

network. In one case, Transco Pipeline (P3) needed to install 75% more pipe links than Kinder Morgan pipeline (P1) to provide service to similar number of customers. Conversely, a pipeline may have a footprint in a region that allows it to efficiently expand its services to new customers, such as Southern Natural pipeline (P2).

The results identify an effect of economies of scale in network expansion under demand-pooling. With respect to this effect, multiple demand points are connected on the same branch, which results in installing fewer pipe links and pressure regulation stations. The results also show that expanding pipelines with a sparse footprint (such as pipeline P3 operated by Transco) results in fewer branches that service multiple customers, thus increasing the utility of the newly added pipeline branches. These results are useful for decision makers and network planners in the gas pipeline industry where network expansion planning is becoming ever more critical, given the increase in industrial demand of natural gas. The results from an experimental study showed that joint decision-making by coal-fired power plants and pipeline companies in determining the timing of activating gas use will be helpful in maximizing the benefits of collaborative expansion of gas transportation networks. Such an approach can maximize the benefits for all parties.

As with any research, there are some limitations of our study. In this study, the benefits of cooperation were evaluated based on economic considerations, i.e., cost-to-serve in terms of expansion of gas transportation networks. This study considered demand and connectivity issues with respect to coal-fired power plants. Additionally, the demand of natural gas for newly installed power plants can also be included. Although power plants are a big consumer group, there are other important consumers of natural gas as well, such as industrial plants, commercial businesses, and residential communities, which may also influence business consideration for pipeline companies and impact their network expansion decisions. Since market dynamics may vary by regions, an extension of this paper would include additional case studies to determine the benefits of the proposed approach across different market segments in the gas transportation industry. This paper evaluates the impact of horizontal cooperation from the point of view of infrastructure expansion costs. Adding considerations for strategic interactions and ways firms compete in the natural gas market would provide another avenue to extend this research.

References

Andre, J., F. Bonnans, and L. Cornibert. "Optimization of Capacity Expansion Planning for Gas Transportation Networks." *European Journal of Operational Research* 197(3), (2009):1019-1027.

Audy, J., S. DAmours and M. Ronnqvist. "An Empirical Study on Coalition Formation and Cost/savings Allocation." *International Journal of Production Economics* 136(1), (2012):13-27.

Audy, J., S. DAmours and L. Rousseau. "Cost Allocation in the Establishment of a Collaborative Transportation Agreement: An Application in the Furniture Industry." *Journal of the Operational Research Society* 62(6), (2010):960-970.

Babonneau, F., Y. Nesterov and J. Vial. "Design and Operations of Gas Transmission Networks." *Operations Research* 60(1), (2012):34-47.

Bahrami, K. "Improving Supply Chain Productivity Through Horizontal Cooperation: The Case of Consumer Goods Manufacturers." *Cost Management in Supply Chains*, (2002):213-232.

Barteau, M. and S. Kota. "Shale Gas: A Game Changer for U.S. Manufacturing." *Energy Institute Report*. University of Michigan, 2014.

Bengtsson, M. and S. Kock. "Cooperation and Competition in Relationships Between Competitors in Business Networks." *Journal of Business & Industrial Marketing* 14(3), (1999):178-194.

Bengtsson, M. and S. Kock. "Coopetition in Business Networks to Cooperate and Compete Simultaneously." *Industrial Marketing Management* 29(5), (2000):411-426.

Bhaskaran, S. and F. Salzborn. "Optimal Design of Gas Pipeline Networks." *Journal of the Operational Research Society*, (1979): 1047-1060.

Caves, R. and M. Porter. "From Entry Barriers to Mobility Barriers: Conjectural Decisions and Contrived Deterrence to New Competition." *The Quarterly Journal of Economics*, (1977): 241-261.

Cruijssen, F., O. Braysy, W. Dullaert, H. Fleuren, and M. Salomon. "Joint Route Planning Under Varying Market Conditions." *International Journal of Physical Distribution & Logistics Management* 37(4), (2007a): 287-304.

Cruijssen, F., M. Cools, and W. Dullaert. "Horizontal Cooperation in Logistics: Opportunities and Impediments." *Transportation Research Part E: Logistics and Transportation Review* 43(2), (2007b):129-142.

Cruijssen, F., W. Dullaert, and H. Fleuren. "Horizontal Cooperation in Transport and Logistics: A Literature Review." *Transportation Journal*, (2007c):22-39.

EIA. "Annual Energy Outlook Report." U.S. Energy Information Administration, 2012.

EIA. U.S. Energy Information Administration URL http://www.eia.gov/, 2013.

Fourer, D., D. Gay, and B. Kernighan. *AMPL: A Modeling Language for Mathematical Programming*. Cengage Learning; 2nd edition, 2002.

Harrigan, K. "An Application of Clustering for Strategic Group Analysis." *Strategic Management Journal* 6(1), (1985):55-73.

INGAA. "Report: Natural Gas Pipeline and Storage Infrastructure Projections Through 2030." Interstate Natural Gas Association of America, 2009.

Kabirian, A. and M. Hemmati. "A Strategic Planning Model for Natural Gas Transmission Networks." *Energy Policy* 35(11), (2007):5656-5670.

Kawatra, R. and D. Bricker. "A Multiperiod Planning Model for the Capacitated Minimal Spanning Tree Problem." *European Journal of Operational Research* 121(2), (2000):412-419.

Kinder Morgan. Natural Gas Pipeline map. Corporate website www.kindermorgan.com , 2014.

Krajewska, M., H. Kopfer, G. Laporte, S. Ropke, and G. Zaccour. "Horizontal Cooperation Among Freight Carriers: Request Allocation and Pro Sharing." *Journal of the Operational Research Society* 59(11), (2007):1483-1491.

Lapides, M., J. Ritchie, A. Benjamin, and S. Malat. "Environmental Rules for U.S. Coal Plants to Impact Multiple Sectors." Goldman Sachs & Co. Report, 2011.

Martin, A., M. Moller, and S. Moritz. "Mixed Integer Models for the Stationary Case of Gas Network Optimization." *Mathematical Programming* 105(2), (2006):563-582.

Mouawad, J. "Estimate Places Natural Gas Reserves 35% Higher." *New York Times*, 2009.

Paltsev, S., H. Jacoby, J. Reilly, Q. Ejaz, J. Morris, F. O'Sullivan, S. Rausch, N. Winchester, and O. Kragha. "The Future of U.S. Natural Gas Production, Use, and Trade." *Energy Policy* 39(9), (2011):5309-5321.

Rios-Mercado, R., S. Wu, L. Scott, and E. Boyd. "A Reduction Technique for Natural Gas Transmission Network Optimization Problems." *Annals of Operations Research* 117(1), (2002):217-234.

Rothfarb, B., H. Frank, D. Rosenbaum, K. Steiglitz, and D. Kleitman. "Optimal Design of Offshore Natural Gas Pipeline Systems." *Operations Research* 18(6), (1970):992-1020.

Schmoltzi, C. and C. Wallenburg. "Horizontal Cooperation Between Logistics Service Providers: Motives, Structure, and Performance." *International Journal of Physical Distribution & Logistics Management* 41(6), (2011):552-575.

Shahidehpour, M., Y. Fu, and T. Wiedman. "Impact of Natural Gas Infrastructure on Electric Power Systems." *Proceedings of the IEEE* 93(5), (2005):1042-1056.

Sollner, A. and M. Rese. "Market Segmentation and the Structure of Competition: Applicability of the Strategic Group Concept for an Improved Market Segmentation on Industrial Markets." *Journal of Business Research* 51(1), (2001):25-36.

Vanovermeire, C., K. Sorensen, A. Breedam, B. Vannieuwenhuyse, and S. Verstrepen. "Horizontal Logistics Collaboration: Decreasing Costs Through Flexibility and an Adequate Cost Allocation Strategy." *International Journal of Logistics Research and Applications*, (2013):1-17.

Vos, G., K. Oerlemans, J. Penninkhof, M. Iding, H. Brummelman, and C. Ruijgrok. "Synergievoordelen in Logistieke Netwerken (Sylonet); Resultaten van een Literatuurinventarisatie." TNO INRO Report, 2002.

Yergin, D. and R. Ineson. "America's Natural Gas Revolution." *The Wall Street Journal*, November 2, 2009.

Zaheer, A., R. Gulati, and N. Nohria. "Strategic Networks." *Strategic Management Journal* 21(3), (2000):203-215.

Zheng, Q., S. Rebennack, N. Iliadis, and P. Pardalos. "Optimization Models in the Natural Gas Industry." *Handbook of Power Systems*, (2010):121-148.

Rafay Ishfaq *is an assistant professor of supply chain management in the Harbert College of Business at Auburn University. He received his Ph.D. degree (2010) from University of Alabama in operations management. Ishfaq's research is focused on exploring interplays among operational, financial, and service issues in distribution, transportation, and supply networks. Combining mathematical modeling and field studies, his research addresses issues related to strategic planning of logistics operations and efficient use of resources within supply chain networks. His research has been published in scholarly journals including* Decision Sciences, European Journal of Operational Research, Transportation Research (Part-E), Journal of Operational Research Society, International Journal of Logistics Research, Computers & Operations Research*, and* Information Resource Management Journal. *Ishfaq's research has been recognized by the Association of European Operational Research Societies with the 2014 Best EJOR Research Paper award, and Science Direct included one of his papers in the 2013 Top-25 Hottest Articles list.*

Mark Clark *has a dual appointment in the Harbert College of Business at Auburn University. He serves as a management scientist in the Auburn Technical Assistance Center and he also serves as a visiting assistant professor in the Management Department. He has a Ph.D. in industrial and systems engineering and specializes in the area of production and operations management. For the last 15 years, Clark has focused primarily on implementing process improvement methodologies in manufacturing and transactional companies. Within the improvement methodologies, his primary interests are predictive modeling and optimization approaches within the initiatives.*

Uzma Raja *is an associate professor of management information systems (MIS) at the University of Alabama. She received her Ph.D. in MIS from Texas A&M University in 2006. Her primary expertise is in the application of business analytics tools and techniques using exploratory research methods. Some of her research projects have been in the area of healthcare, software development, financial systems, and energy sector. Raja's research has been published in journals such as Decision Sciences, IEEE Transactions on S*oftware Engineering, Empirical Software Engineering, Journal of Software Maintenance, Information *and* Technology Management *and* Information Resource Management Journal. *She is an active member of the AIS community and the special interest group on business analytics.*

Multi-Vehicle Crashes Involving Large Trucks: A Random Parameter Discrete Outcome Modeling Approach

by Mouyid Islam

A growing concern on large-truck crashes increased over the years due to the potential economic impacts and level of injury severity. This study aims to analyze the injury severities of multi-vehicle large-trucks crashes on national highways. To capture and understand the complexities of contributing factors, two random parameter discrete outcome models – random parameter ordered probit and mixed logit – were estimated to predict the likelihood of five injury severity outcomes: fatal, incapacitating, non-incapacitating, possible injury, and no-injury. Estimation findings indicate that the level of injury severity is highly influenced by a number of complex interactions of factors, namely, human, vehicular, road-environmental, and crash dynamics that can vary across the observations.

INTRODUCTION

Very few studies have addressed freight transport safety with regard to injury analysis of crashes involving large trucks from an econometric modeling standpoint (Islam and Hernandez 2011, Islam and Hernandez 2012, Chen and Chen 2011, Zhu and Srinivasan 2011, Lemp et al. 2011), specifically, multi-vehicle crashes in which large trucks are involved. A more recent safety fact by NHTSA (2011) indicated that 81% of fatal crashes involving large trucks are multi-vehicle crashes in contrast with 58% for crashes involving passenger vehicles. A clear evidence of large trucks being more likely to be involved in a fatal multi-vehicle crash compared to a fatal single-vehicle crash (NHTSA 2011), is a growing concern for highway safety engineers, trucking companies, policy makers, and overall public due to the magnitude and devastation associated with these crashes.

Numerous studies have been conducted on crash frequency (Ivan et al. 1999, Ivan et al. 2000, Geedipally and Lord 2010) models rather than severity likelihood models. Those studies focusing on severity models indicated that multi-vehicle crashes are more severe than single-vehicle crashes in particular conditions (Viano et al. 1990) but not with regard to large trucks (Viano et al. 1990, Jung et al. 2012, Savolainen and Mannering 2007). A study by Viano (1990) emphasized the injury severities in multi-vehicle crashes mostly occurred on dry surface, daylight hours and non-alcohol involvement, from side-impacts based on the National Crash Severity Study. Moreover, Jung et al. (2012) modeled injury severity for multi-vehicle crashes which occur more frequently than single-vehicle crashes in rainy weather, using time of day, rainfall intensity, water film depth, and deficiency of car-following distance. Ivan et al. (1999) developed a Poisson regression model and found that multiple vehicle crashes are highly related with increase of traffic intensity, shoulder width, truck percentage, and traffic signals based on studies of two-lane rural highways in Connecticut. Considering injury mechanism involving large trucks with other vehicles, the contributing factors in multi-vehicle crashes are quite different in nature from single-vehicle crashes because of the differences in driving behavior, vehicle operating characteristics, and maneuverability by different groups of vehicles (Ivan et al. 1999, Chen and Chen 2011, Geedipally and Lord 2010). Since the vehicular form and mass incompatibility between large trucks and passenger vehicles are high in multi-vehicle crashes, the level of severity sustained is significant as is the associated societal cost.

Departing from traditional modeling approaches such as fixed parameter models focusing on the injury severities, advanced econometric modeling approach was explored by emphasizing the unobserved factors hidden in the process of crash reporting by the investigating police officers at the crash scene, and data sampling scheme within the stored database. Mixed logit and random parameter ordered probit models were developed to shed light on the contributing factors leading to multi-vehicle crashes involving large trucks. Fusing three datasets of the National Automotive Sampling System – General Estimated System (NASS-GES) from 2005 to 2008 to obtain a crash sample, this study aims at providing a better understanding of the complex interactions of contributing factors influencing injury outcomes (i.e., fatal, incapacitating injury, non-incapacitating injury, possible injury, and no-injury) in crashes involving large trucks. To capture these complexities using NASS-GES, consideration of random parameters provides a mechanism to account for any unobserved heterogeneity that may exist, indicating unobserved factors that may vary across observations. This unobserved heterogeneity can be explained in such a way that each observation in the dataset vary from each other in the entire sample (Kim et al. 2010) and there may be cases of limited data such as roadway geometrics, pavement condition, and general weather and traffic characteristics (Anastasopolus and Mannering 2010).

Although both of the models (i.e., mixed logit and random parameter ordered probit models) have been applied to large truck crash severity analysis from different modeling perspectives, this research extends the current literature by introducing additional significant variables related to human factors in regard to multi-vehicle large truck crashes on US Interstate 1. From the standpoint of practical applications, the models indicating any critical factors such as human, vehicular, and road-environment should be considered for the implementation of possible countermeasures by the safety engineers, policy makers, trucking companies, and other stakeholders. The statistical models based on the comprehensive historical crash data focusing on multi-vehicle crashes involving large trucks on the interstates can be used as an analytical tool to identify the factors for possible countermeasures. A specific countermeasure against severe injury crashes involving large trucks related to fatigued drivers can be undertaken by installing new and increasing efficiency of existing parking spaces and installing rumble strips in new and existing roadways (NCHRP 500 2004). The paper focuses on the sample size and descriptive statistics of the important variables in the Empirical Setting section as well as modeling techniques in the Methodology section and model results in the Empirical Results section. Then, the model results are discussed in terms of contributing factors leading to multi-vehicle crashes involving large trucks with marginal effect estimates from both models. A conclusion was drawn from the results and future work to be done to improve the sample and model results is discussed.

EMPIRICAL SETTINGS

The data for crashes involving large trucks were obtained from the nationwide NASS-GES crash database maintained by National Highway Traffic Safety Administration (NHTSA). A large truck is commonly classified as a tractor-trailer, single-unit truck, or cargo van having a Gross Vehicle Weight Rating (GVWR) greater than 10,000 pounds (IIHS 2009). The GES database is based on a nationally representative probability sample selected from the estimated 5.8 million police-reported crashes resulting in a fatality or injury and those involving major property damage annually (NASS-GES 2008). It is traditional to analyze injury severity utilizing police reported crash data. However, this police reported crash data are generally subjected to under reporting in the case of minor or no personal injury, as evidenced from a technical report by NHTSA (2009) that 25% of minor injury crashes and 50% of no injury crashes are unreported (Savolainen et al. 2011). In this study, a subset of 6,588 observations was used for large truck involved crashes over a period of four years (i.e., 2005 to 2008) from an annual average of 56,970 total crashes over this time period (also includes truck-truck crashes). Despite the issues of under reporting for minor and no personal injury crashes along

with the multi-stage sampling scheme in the GES database, GES focuses on the crashes of greatest concern to the highway safety community and general public (NASS-GES 2008). As a result, GES is a representative sample of the crashes from the police reports all over the United States and it is fairly common practice in the modeling approach to assume that sample data selected from the population have equal likelihood of being considered in the sample (Savolainen et al. 2011).

To investigate contributing human, vehicle, and road-environment factors, a sample of 6,588 data observations representing crashes involving at least a large truck and other vehicles (i.e., number of vehicles involved is two or more than two) on the interstate highway system from 2005 to 2008 were extracted from the NASS-GES database. The maximum level of injury severity recorded in the vehicle or person dataset was aggregated to represent a crash. Each observation in the sample is a crash representing the maximum level of injury of the occupants, involving at least one large truck with one or more vehicles on interstate highways. The crash dataset was fused to the vehicle and person datasets through appropriate linking variables such as crash number; while the vehicle and person dataset were linked through the vehicle and crash number using the Statistical Analysis System (SAS). The mixed logit and ordered probit frameworks were modeled in Limdep (NLOGIT 4.0).

The expected and modeled effects of the explanatory variables are shown in Table 1 for Ordered Probit model and in Table 2 for Mixed Logit model. The expected effects for the variables are based on the previous safety studies and the analyst's (i.e., author's) general understanding on the outcomes of the crashes under given conditions (such as wet surface, time of day, month of year, curved section, distraction, crash types, etc.). In the perspective of multi-vehicle large truck involved crashes, the collision partners range from single passenger vehicles to multiple passenger vehicles or trucks. The expected effects of the variable follows the general trend in term of injury outcomes of large truck involved crashes.

Out of 15 variables, only four were found to have opposite than expected effects in random parameter ordered probit model. Similarly, out of 22 variables, only three were found to have opposite than expected effects.

1. Single-unit trucks are found to be involved in less severe crashes. However, the expectation is opposite – more severe crashes. This is because single-unit trucks are comparatively easier to maneuver than double-unit trucks. As such, the drivers of single-unit trucks are less cautious than those of double-unit trucks. The chances are single-unit trucks would be highly involved in more severe crashes because of flexibility of maneuvering in higher speed than double-unit trucks.
2. In the event of rollover, the likelihood of being severely injured is higher. However, that likelihood of being severely injured is only the case for passenger vehicle occupants, when being struck by large trucks coupled with not being properly restrained by seat-belts. However, that may not be true for large truck occupants. And this is reflected in the sign of the variable – decreasing effect.
3. The presence of passengers in the vehicles increases the chances of being severely injured for passenger vehicle being struck by large trucks. Higher occupancy increases the likelihood of being severely injured for passenger vehicles compared with large trucks.
4. In the event of rollover, the likelihood of having incapacitating injury (A-type) is higher. However, that likelihood of having A-type injury is the case for passenger vehicle occupants, when being struck by large trucks coupled with not being properly restrained by seat-belts. However, that may not be true for large truck occupants. And this is reflected in the sign of the variable – decreasing effect.
5. When the road surface is wet, drivers tend to slow down to adjust to the ambient environmental conditions. So, the likelihood of possible injury to passenger vehicle occupants should be less. However, the chances of other injury levels can increase as well. On the other hand, multi-vehicle collisions between large trucks and passenger vehicles

Table 1: Expectation on Signs of Explanatory Variables of Random Parameter Ordered Probit Model

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Weather condition (1 if snow, 0 otherwise)	Decreasing effect	Decreasing effect	In snowy weather drivers would be more cautious.
Months of the year (1 if summer months (June - August), 0 otherwise)	Increasing effect	Increasing effect	Because of better weather, there is a tendency to travel more and thus exposure level increases.
Light condition of street (1 if dark, 0 otherwise)	Increasing effect	Increasing effect	In dark condition, drivers face difficulty is terms of visibility.
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation above.
Vehicle role (1 if struck by other vehicle, 0 otherwise)	Decreasing effect	Decreasing effect	If large truck is struck by other vehicles, there will less of energy absorption by the trucks than by the passenger vehicles because of momentum.
The most harmful event (1 if rollover, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation above.
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	Decreasing effect	Decreasing effect	Same direction side swipe may not results in serious injury than opposite direction.
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	Decreasing effect	Decreasing effect	Lane changing maneuver may not result in serious injury because of vehicles are changing between lanes.
Vehicle maneuver just prior to impending crash (1 if going straight, 0 otherwise)	Decreasing effect	Decreasing effect	One of the two or multiple vehicles involved in the crashes, is keeping the lane (i.e., going straight) while other vehicles are changing lanes. This maneuver results in low severe crashes.
Factor of crash identified in the investigation (1 if speed, 0 otherwise)	Increasing effect	Increasing effect	Speeding for the conditions very likely result in serious injury crashes.
Driver's attention level at the time of impending crash (1 if distraction or inattention, 0 otherwise)	Increasing effect	Increasing effect	Driver's distraction can very likely lead to serious injury crashes because of not paying required level of attention to drive and maintain safe distance between vehicles.

(Table 1 continued)

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	Increasing effect	Increasing effect	Not using seat-belt can lead to serious injury crashes because of unbelted occupants can eject from the vehicles and secondary impacts of occupants' body inside the vehicle compartment can cause serious injuries.
Location of the occupants in the vehicle (1 if for passenger position, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation above.
Gender of the occupants (1 if male, 0 otherwise)	Decreasing effect	Decreasing effect	Male drivers/occupants are less likely to be involved in severe crashes than female counter parts because of different body tolerance against the sustained injury levels.
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	Increasing effect	Increasing effect	Because of border state and wide landscape of rural and urban interstate system in Texas, drivers drive relatively relaxed with higher speeds. Also, drivers from border regions may not be familiar with road network and driving behavior is very different.

Table 2: Expectation on Signs of Explanatory Variables of Mixed Logit Model

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Fatal Outcome			
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	Increasing effect	Increasing effect	Getting departed from the roadway increases in the risk of getting hit by the roadside fixed objects as well as the rollover (because of steep slope and tipping point and speed).
Light condition of street (1 if dark, 0 otherwise)	Increasing effect	Increasing effect	Dark roadway condition clearly poses more risk if terms of visibility for the drivers in the high speed roadway.
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	Increasing effect	Increasing effect	Head-on collision increases the risk of crashes result in severe injuries.
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	Increasing effect	Increasing effect	This relates the fatigue/sleepy driving condition (after lunch time) during the day.
Incapacitating Injury Outcome			
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	Increasing effect	Increasing effect	Distracted driving obviously increases the risk of crashes that results in severe crashes.
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	Increasing effect	Increasing effect	Tire-related malfunctions increase the instability of keeping the vehicle on the road and increases the crashes resulting in severe injuries.
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation below
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	Increasing effect	Increasing effect	Rear-end crashes increases the severe injuries crashes – passenger vehicles hitting the rear of large trucks, where the height of large truck with its form and mass incompatibility force intrudes into the passenger vehicle and same is true for otherwise (large truck hitting passenger vehicles).

(Table 2 continued)

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Time of the day (1 if 5 am in the morning, 0 otherwise)	Increasing effect	Increasing effect	Its early morning traffic in high speed facility which increases the severe injury crashes.
Non-incapacitating Injury Outcome			
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	Increasing effect	Increasing effect	Not using seat-belt can lead to serious injury crashes because of unbelted occupants can eject from the vehicles and secondary impacts of occupants' body inside the vehicle compartment can cause serious injuries.
Time of the day (1 if 4 am in the morning, 0 otherwise)	Increasing effect	Increasing effect	Its early morning traffic in high speed facility which increases the severe injury crashes.
Months of the year (1 if summer months (June to August), 0 otherwise)	Increasing effect	Increasing effect	Because of better weather, there is a tendency to travel more on roads and thus exposure level increases.
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	Decreasing effect	Decreasing effect	Side-swipe (same direction) increases the likelihood of property-damage-only or lower severity crashes. But, that does not results in severe injury crashes.
Possible Injury Outcome			
Gender of the occupants (1 if male, 0 otherwise)	Decreasing effect	Decreasing effect	Male drivers/occupants are less likely to be involved in severe crashes than female counter parts because of different body tolerance against the sustained injury levels.
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	Increasing effect	Increasing effect	Because of border state and wide landscape of rural and urban interstate system in Texas, drivers drive relatively relaxed with higher speeds. Also, drivers from border regions may not be familiar with road network and driving behavior is very different.
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	Increasing effect	Increasing effect	Speeding for the conditions very likely result in serious injury crashes.

(Table 2 continued)

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Number of vehicles involved in the crash	Increasing effect	Increasing effect	Higher the number of vehicles involved in the large truck involved crashes, the higher likelihood of being injured.
Road surface condition (1 if wet, 0 otherwise)	Increasing effect	Decreasing effect	See the explanation below.
Non-injury Outcome (Property-Damage-Only)			
Alignment of highway section (1 for curved section, 0 otherwise)	Decreasing effect	Decreasing effect	Driving along the curve under the unfavorable weather, lighting, and distraction makes drivers aware of the risk associated in driving along that segment.
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation below.
Light condition of street (1 if the surrounding area is dark but outside is lighted, 0 otherwise)	Increasing effect	Increasing effect	Some section of high speed roadways may have lighting but some places lacks proper lighting and the surrounding place providing lighting to the high-speed motorist is not enough to avoid the risk at night time driving.
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	Increasing effect	Increasing effect	Lane changing maneuver may not result in serious injury because of vehicles are changing between lanes. But, it can results in lower to no-injury crashes.
Driver's attention level at the time of pre-crash (1 if sleepy, 0 otherwise)	Decreasing effect	Decreasing effect	Sleepy or fatigued driving obviously increases the risk of crashes that results in severe crashes (alternatively decreases the likelihood of lower severity crashes)
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	Increasing effect	Increasing effect	Single-unit trucks comparatively easier to maneuver than double-unit trucks. As such, the drivers of single-unit trucks are less cautious than those of double-unit trucks. The chances are single-unit trucks would be highly involved in non-severe crashes because of flexibility of maneuvering in higher speed than double-unit trucks.

could possibly result in some level of injury given at lower speed, and may still have higher potential for possible injury.

6. In the case of rear-end collision, there is higher likelihood of property-damage-only crashes but it also may cause higher chances of other injury levels such as A-, B-, and C-injury levels.

In summary, the variables are defined from data sources and they are found to be statistically significant in large truck modeling.

Table 3 and Table 4 show the descriptive statistics of key variables in the models[2]. Although some of the variables are common in both models, the data description of some important variables is presented here. With regard to random parameter ordered probit model, Table 3 illustrates about 33% of the observations related to side-swipes in the same directions, 81% related to rollover crashes. Additionally, as seen from Table 3, lane changing maneuvers account for 12% of the total observations compared with 65.2% regarding going straight. Another key observation is that dark conditions and summer months (i.e., June to August) account for 11% and 23.5% of the multi-vehicle crashes, respectively. The statistics further illustrate that speeding and being struck by other vehicles account for about 8% and 46.6% of the total observations in multi-vehicle crashes, respectively.

Table 3: Descriptive Statistics of Key Variables in Ordered Probit Model

Meaning of Variables in the Model	Mean	Std. Dev.
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	0.041	0.199
Light condition of street (1 if dark, 0 otherwise)	0.109	0.312
Passenger role (1 if passenger is present, 0 otherwise)	0.977	0.146
Vehicle maneuver during pre-crash situation (1 if going straight, 0 otherwise)	0.652	0.476
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	0.041	0.197
Role as crash partner (1 if struck, 0 otherwise)	0.466	0.498
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	0.809	0.392
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.331	0.471
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	0.018	0.133
Months of the year (1 if summer months (June to August), 0 otherwise)	0.235	0.424
Gender of the occupants (1 if male, 0 otherwise)	0.938	0.240
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.100	0.300
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	0.079	0.270
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.118	0.323
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.750	0.432

Table 4 shows that about 42.4% of the total crash observations related to rear-end crashes and on average more than two (2.3) vehicles were involved in multiple vehicle crashes. The statistics as seen in Table 4 illustrate that lane changing, inattentive driving, and dark conditions account for

11.8%, 4.1%, and 11% of the total crash observations, respectively. Curved sections of highways and wet pavement account for 8.1% and 15.2% of total crash observations, respectively. The time specific variables such as summer month (i.e., June to August) and time of day (2 pm and 5 am) on average account for 23.5%, 5.5%, and 12.3% of total crash observations, respectively.

Table 4: Descriptive Statistics of Key Variables in Mixed Logit Model

Meaning of Variables in the Model	Mean	Std. Dev.	Outcome
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	0.009	0.098	Fatal (K)
Light condition of street (1 if dark, 0 otherwise)	0.109	0.312	
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	0.008	0.093	
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	0.055	0.228	
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	0.041	0.197	Incapacitating Injury Crash (A)
Time of the day (1 if 5 am in the morning, 0 otherwise)	0.123	0.328	
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	0.007	0.085	
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	0.424	0.494	
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	0.809	0.392	
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.331	0.470	Non-Incapacitating Injury Crash (B)
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	0.018	0.133	
Time of the day (1 if 4 am in the morning, 0 otherwise)	0.020	0.141	
Months of the year (1 if summer months (June to August), 0 otherwise)	0.235	0.424	
Gender of the occupants (1 if male, 0 otherwise)	0.938	0.240	Possible Injury (C)
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.100	0.300	
Number of vehicles involved in the crash	2.324	0.672	
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	0.079	0.270	
Road surface condition (1 if wet, 0 otherwise)	0.152	0.359	
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.118	0.323	No-injury (PDO)
Light condition of street (1 if the surrounding area is dark but outside is lighted, 0 otherwise)	0.157	0.364	
Driver's attention level at the time of impending crash (1 if sleepy, 0 otherwise)	0.002	0.042	
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.751	0.432	
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	0.424	0.494	
Alignment of highway section (1 for curved section, 0 otherwise)	0.081	0.274	

The correlation matrix for both of the injury severity models was computed. The correlation matrix for the random parameter ordered probit model indicates that lane changing maneuver has a correlation coefficient of 0.501 and 0.329 with going straight and side-swipe crashes, respectively. On the other hand, the correlation matrix for mixed logit model indicate that rear-end collision has a correlation coefficient of 0.604 with side-swipe crashes, and time – four o'clock has correlation coefficient of 0.385 with five o'clock. Although the magnitude of the coefficients might pose some multicollinearity issues, the lane changing maneuver and crashes are not seriously correlated in the models. For the random parameter ordered probit model, a lane changing maneuver might result in subsequent actions of going straight and side-swipe in the same direction in a multi-vehicle collision. The same is true for the mixed logit model where rear-end collision might be the outcome of some subsequent actions of a side-swipe collision. Also, the early morning hours from four to five o'clock account for severe injuries for multi-vehicle crashes.

METHODOLOGY

In order to achieve a better understanding of the injury severity of large trucks involved in multi-vehicle crashes with discrete outcome models, random parameter ordered probit and mixed logit models were developed.

Ordered Probit Framework

A random parameter ordered probit model was developed to capture the injury severity experienced while accounting for unobserved heterogeneity (McKelvey and Zavoina 1975, Chistoforou et al. 2010, Zhu and Srinivasan 2011) because of the ordinal nature of injury according to the KABCO scale (i.e., 'K' for Fatal, 'A' for Incapacitating injury, 'B' for Non-incapacitating injury, 'C' for Possible injury, and 'O' for Property-Damage-Only). In this study, the descending order (i.e., 0 for K , 1 for A, 2 for B, 3 for C, and 4 for O) (Islam and Hernandez 2012) was followed rather than ascending order in the previous studies (Chistoforou et al. 2010, Abdel-Aty 2003, Gray et al. 2008, Kockelman and Kweon 2002, Lee and Abdel-Aty 2005, O'Donnell and Connor 1996, Pai and Saleh 2008, Quddus et al. 2002, Xie et al. 2009, Zajac and Ivan 2002) to account for any bias resulting from under-reporting tendency in the crash and variability of parameter estimation (Ye and Lord 2011).

In the formulation of the model, an unobserved variable is a modeling basis of ordinal ranking of the data, with specified as a latent and continuous measure of injury severity of each observation (Washington et al. 2011):

(1) $y^* = \boldsymbol{\beta X} + \varepsilon$

where:

- y^* : is the dependent variable (specified as a latent and continuous measure of injury severity of each observation n),
- $\boldsymbol{\beta}$: is a vector of estimable parameters,
- $\boldsymbol{X}$: is a vector of explanatory variables (e.g., human, roadway segment, vehicle, and crash mechanism characteristics),
- ε : is a random error term (assumed to be normally distributed with zero mean and a variance of one).

Using Equation 1, and under the order probit framework the observed ordinal data y (e.g., injury severity) for each observation can be represented as (Washington et al. 2011):

$$
(2)\quad \begin{array}{ll}
y = 0 & if\ \infty \le y^* \le \mu_0 \\
y = 1 & if\ \mu_0 \le y^* \le \mu_1 \\
y = 2 & if\ \mu_1 \le y^* \le \mu_2 \\
y = I - 1 & if\ \mu_{I-2} \le y^* \le \mu_{I-1} \\
y = I & if\ \mu_{I-1} \le y^* \le \infty
\end{array}
$$

where:

μ : are estimable parameters (i.e., thresholds) that define y and are estimated jointly with the model parameters $\boldsymbol{\beta}$, which corresponds to integer ordering, and I is the highest integer ordered response (e.g., PDO which is 4).

To estimate the probabilities of I specific ordered response for each observation n, ε is assumed to be normally distributed with zero mean and variance of one. The ordered probit model with ordered selection probabilities is defined as follows:

$$
(3)\quad \begin{array}{l}
P_n(y = 0) = \Phi(-\boldsymbol{\beta X}) \\
P_n(y = 1) = \Phi(\mu_1 - \boldsymbol{\beta X}) - \Phi(-\boldsymbol{\beta X}) \\
P_n(y = 2) = \Phi(\mu_2 - \boldsymbol{\beta X}) - \Phi(\mu_1 - \boldsymbol{\beta X}) \\
P_n(y = 3) = \Phi(\mu_3 - \boldsymbol{\beta X}) - \Phi(\mu_2 - \boldsymbol{\beta X}) \\
P_n(y = 4) = \Phi(\mu_4 - \boldsymbol{\beta X}) - \Phi(\mu_3 - \boldsymbol{\beta X}) \\
P_n(y = I) = 1 - \Phi(\mu_{I-1} - \boldsymbol{\beta X})
\end{array}
$$

where:

$P_n(y = I)$: is the probability that observation has as the highest ordered-response index (in our case PDO being 4 is the highest)

$\Phi(\cdot)$: is the standard normal cumulative distribution function

Marginal effects are computed at the sample mean for each category (Greene 2007, Washington et al. 2010):

$$
(4)\quad \frac{P_n(y = I)}{\partial \boldsymbol{X}} = [\phi(\mu_{I-2} - \boldsymbol{\beta X}) - \phi(\mu_{I-1} - \boldsymbol{\beta X})]\boldsymbol{\beta}
$$

where:

$\phi(\cdot)$: is the probability mass function of the standard normal distribution

Greene (2007) developed an estimation procedure that utilizes simulated maximum likelihood estimation to incorporate random parameters in the ordered probit modeling scheme. The random parameter ordered probit model is formulated by taking into account an error term being correlated with the unobserved factors in ε_i (as shown in Equation 1), which translates the individual heterogeneity into parameter heterogeneity,[3] as follows (Greene 2007):

$$
(5)\quad \beta_{in} = \beta + \gamma_{in}
$$

where:

β_{in} : is vector of parameters that can be estimated of each driver–injury outcome i in observation n.

γ_{in} : is randomly distributed term (for example a normally distributed term with mean zero and variance σ^2).

This parameter heterogeneity results from the uncertainty of β_{in} for a number of factors. These include the data collection process by the investigating police officers at the crash scene, objective

information of a particular parameter as opposed to incomplete and qualitative information gathered or inferred from the secondary sources.

Mixed Logit Framework

In terms of utility functions and other methodological flexibility, a mixed logit model was developed that can be used to determine the contributing factors that influence the likelihood of severity outcomes in large truck involved crashes.

S_{in} is a linear function that determines discrete outcome *i* as injury severity outcome such as fatality, incapacitating injury, non-incapacitating injury, possible injury, and no-injury (property-damage-only) for observation *n* such that: (Washington et al. 2011):

$$(6)\quad S_{in} = \boldsymbol{\beta}_i \mathbf{X}_{in} + \varepsilon_{in}$$

where:

$\boldsymbol{X}_{in}$: is vector of explanatory variables covering driver, vehicle, and road and environmental factors that determine injury outcome (*i*),

β_i : is vector of estimable parameters,

ε_{in} : is random error.

If ε_{in}'s are assumed to be generalized extreme value distributed (or Gumble distributed) with a possible limit distribution of properly normalized maxima of a sequence of independent and identically distributed random variables, McFadden (1981) has shown that the multinomial logit results such that

$$(7)\quad P_n(i) = \frac{EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_I EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]}$$

where:

$P_n(i)$: is probability of observation *n* having severity outcome *i* (such as fatality, incapacitating injury, non-incapacitating injury, possible injury, PDO) ($\in$ *I* with *I* denoting all possible outcomes of injury severity for observation *n*).

The NASS-GES crash database is likely to have a significant amount of unobserved heterogeneity. As the investigating police officers report factors influencing the injury severity outcome differently due to officers' discretion when reporting estimates of the representative crash data sample all over the United States. The possibility that elements of the parameter vector may vary across observations of each crash was considered by using a random parameters logit model (also known as the mixed logit model). Previous works by McFadden and Rudd (1994), Geweke et al. (1994), Revelt and Train (1997, 1999), Train (1997), Stern (1997), Brownstone and Train (1999), McFadden and Train (2000), and Bhat (2001) have shown the development and effectiveness of the mixed logit model approach can account for the variations across crash observations of the effects that variables have on the injury severity outcomes considered in this study. The mixed logit model is written as (Train 2003),

$$(8)\quad P_n(i) = \int \frac{EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_I EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]} f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}) d\boldsymbol{\beta}_i$$

where:

$f(\boldsymbol{\beta}i|\boldsymbol{\varphi})$: is the density function of $\boldsymbol{\beta}i$, $\boldsymbol{\varphi}$ is a vector of parameters of the density function (mean and variance), and all other terms are as previously defined.

This model can now account for the injury severity outcome of specific variations of the effect of $\mathbf{X}_{in}$ on injury severity outcome probabilities, with the density function $f(\boldsymbol{\beta}\mathbf{i}|\boldsymbol{\varphi})$ used to determine $\boldsymbol{\beta}_i$. Mixed logit probabilities are then a weighted average for different values of $\boldsymbol{\beta}_i$ across crash observations where some elements of the vector $\boldsymbol{\beta}_i$ may be fixed and some randomly distributed. If the parameters are random, the mixed logit weights are determined by the density function $f(\boldsymbol{\beta}i|\boldsymbol{\varphi})$ (Milton et al. 2008, Washington et al. 2011).

In order to estimate the impact of particular variables on the injury-outcome likelihood, elasticities (or direct-pseudo elasticity) are computed. In the context of the current injury severity model, most of the variables are indicator (i.e., 1 or 0) in nature. Direct-pseudo elasticities are estimated to measure the marginal effects of indicator variables when any particular indicator variable switches from 0 to 1 or vice versa (Washington et al. 2011). This is translated to a percentage change of the injury-outcome likelihood when the indicator variable switches between 0 and 1 or 1 to 0. For binary indicator variables, the direct-pseudo elasticity is estimated as shown in Equation (10) (Kim et al. 2010):

$$(9)\quad E_{x_{nk}(i)}^{P_n(i)} = \frac{P_n(i)[given\ x_{nk}(i) = 1] - P_n(i)[given\ x_{nk}(i) = 0]}{P_n(i)[given\ x_{nk}(i) = 0]}$$

where:

$P_n(i)$: is given the Equation (8) and simulated as shown in Equation (11).
$x_{nk}(i)$: is the k-th independent variable associated with injury severity i for observation n.

Direct average elasticities of any continuous variable are estimated using Equation 10. This measures the percentage change is injury outcome likelihood when the continuous variable changes one unit (Washington et al. 2011).

$$(10)\quad E_{x_{nki}}^{P_n(i)} = \frac{\frac{\partial P_n(i)}{P_n(i)}}{\frac{\partial x_{nk(i)}}{x_{nk(i)}}} = \frac{\partial P_n(i)}{P_n(i)} \cdot \frac{x_{nk(i)}}{\partial x_{nk(i)}}$$

where:

$P_n(i)$: is given the Equation (8) and simulated as shown in Equation (11).
$x_{nk}(i)$: the k-th independent variable associated with injury severity i for observation n.

The unconditional probability in Equation (8) (Kim et al. 2010) can be estimated with an unbiased and smooth simulator (McFadden and Train 2000) that is computed as (Walker and Ben-Akiva 2002, Kim et al. 2010):

$$(11)\quad \hat{P}_n(i) = \frac{1}{R}\sum_{r=1}^{R} P_{in} = \frac{1}{R}\sum_{r=1}^{R} \int \frac{EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_I EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]} f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}) d\boldsymbol{\beta}_i$$

where:

R : is the total number of draws (systematic non-random sequence of numbers – Halton draws).

Since the direct pseudo-elasticity is calculated for each observation, it is usually reported as the average direct pseudo-elasticity (taking average over the sample) as a measure of the marginal effect of an indicator variable on the likelihood of a particular injury severity outcome (Kim et al. 2010).

With the simulator in Equation (11), Maximum Simulated Likelihood Estimation (MSLE) can be used to estimate parameters, and this MSLE estimator is asymptotically normal and consistent (Lee 1992, Kim et al. 2010):

(12) $max_{\boldsymbol{\beta_{in}}} \sum_{n=1}^{N} \sum_{i=1}^{I} y_{in} ln\hat{P}_n(i)$

where:

N : is the total number of observations (i.e., crashes in the sample)

y_{in} : is 1 if individual n suffers from injury severity i, 0 otherwise.

Maximum likelihood estimation with random parameters of both mixed logit and random parameter ordered probit models is undertaken with simulation approaches due to the difficulty in computing the probabilities (Halton 1960, Train 1999, Bhat 2003, Milton et al. 2008, Anastasopoulos and Mannering 2009). The most widely accepted simulation approach utilizes Halton draws, which is a technique developed by Halton (1960) to generate a systematic non-random sequence of numbers. Halton draws have been shown to provide a more efficient distribution of the draws for numerical integration than purely random draws (Bhat 2003, Train 1999, Christoforou et al. 2010). In both of the random parameter models, 200 Halton draws were applied to estimate parameters using maximum simulated likelihood estimation.

EMPIRICAL RESULTS

The variables in both estimated models were found to be statistically significant within a 95% and 90% confidence level for random parameter ordered probit and mixed logit models, respectively.

A random parameter ordered probit and mixed logit model was developed based on fixed parameter ordered probit and initial multinomial logit model, respectively. The random parameter ordered probit model and mixed logit model were found to be statistically superior models (i.e., fixed parameter ordered probit model and multinomial logit model) as evidenced from the following hypothesis and likelihood ratio test.

(13) $\chi^2 = -2 * [LL_{FIX}(\beta^{FIX}) - LL_{RAN}(\beta^{RAN})]$

where:

$LL_{FIX}(\beta^{FIX})$: is the log-likelihood at convergence of the fixed parameters model (-3032.560)

$LL_{RAN}(\beta^{RAN})$: is the log-likelihood at convergence of the random parameters model (-3022.542)

$\chi^2 = 20.036$ (5 degree of freedom)

The Chi-square statistic for the likelihood ratio test with five degrees of freedom gave a value greater than the 99.88% ($\chi^2 = 20.036$) confidence interval. This confidence interval indicates that the random parameter model is statistically superior to the corresponding fixed parameter models.

(14) $\chi^2 = -2 * [LL_{MNL}(\beta^{MNL}) - LL_{ML}(\beta^{ML})]$

where:

$LL_{MNL}(\beta^{MNL})$: is the log-likelihood at convergence of the multinomial logit model (-3087.115)

$LL_{ML}(\beta^{ML})$: is the log-likelihood at convergence of the mixed logit model (-3081.050)

$\chi^2 = 12.13$ (with 3 degree of freedom)

The Chi-square statistic for the likelihood ratio test with three degrees of freedom gave a value greater than the 99.31% (χ^2 = 12.13) confidence interval. This confidence interval indicates that the random parameter model is statistically superior to the corresponding fixed parameter model (i.e., multinomial model). In both cases above, this means that the null hypothesis of the random parameter models (i.e., mixed logit and random parameter ordered probit) are no better than the fixed models (i.e., multinomial and ordered probit model) is rejected.

The human, vehicle, and road-environment contributing factors as well as crash mechanisms in the multi-vehicle large truck involved crashes are described below as found in the model results shown in Table 5 and Table 6.

There are five parameters found to be random in the random parameter ordered probit model. These five random parameters are constant, dark condition, side-swipe collision (same direction), lane changing maneuver, and being male occupants. The first parameter – constant, having mean of 6.088 and standard deviation of 3.672, has 4.87% observations below zero (i.e., 91.13% above zero). This captures significant unobserved heterogeneity present in sample data. The second parameter – dark condition, having mean of -0.269 and standard deviation of 2.223, has 54.82% observations below zero (i.e., 45.18% above zero). This indicates that 54.8% multiple vehicle large truck crashes in the dark condition resulted in severe injuries. The third parameter – side-swipe collision (same direction), having mean of 1.251 and standard deviation of 1.004, has 10.64% of observations below zero (i.e., 89.36% above zero). This indicates that 89.4% of multiple vehicle large truck collision as side-swipe (same direction) resulted in less severe injuries. The fourth parameter – lane changing maneuver, having mean of 2.617 and standard deviation of 3.119, has 20.1% observations below zero (i.e., 79.9% above zero). This indicates that 79.9% of multiple vehicle large truck crashes as consequences of lane changing maneuver resulted in less severe injuries. The fifth parameter – male occupants, having mean of 0.719 and standard deviation of 0.546, has 9.4% observations below zero (i.e., 89.6% above zero). This indicates that 89.6% of multi-vehicle large truck crashes involving male occupants experienced less severe injuries. The estimated model results are presented in Table 5.

Since no-injury (i.e., PDO) is a base condition in the mixed logit model, the estimated results presented in Table 6 are the difference between the target injury outcomes (i.e., fatal, incapacitating, non-incapacitating, and possible injury outcome) with respect to base condition (i.e., PDO). There are three random parameters found statistically significant in mixed logit model. The constant specific to fatality, having a mean of -8.729 and standard deviation of 2.663, has 99.95% of observations below zero. This captures some unobserved heterogeneity present in the fatal outcome in multiple vehicle large truck involved crashes.

Table 5: Multi-Vehicle Random Parameter Ordered Probit Model Results

Injury Severity – Random Parameter Ordered Probit	Random Parameters Model		
	Coeff.	*t*-stat	*P*-value
Constant	6.088	18.889	0.000
Standard Deviation of parameter distribution	*3.672*	*34.078*	*0.000*
Weather condition (1 if snow, 0 otherwise)	0.861	4.344	0.000
Months of the year (1 if summer months (June - August), 0 otherwise)	-0.580	-7.484[	0.000
Light condition of street (1 if dark, 0 otherwise)	-0.269	-2.137	0.033
Standard Deviation of parameter distribution	*2.223*	*17.636*	*0.000*
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	1.402	17.427	0.000
Vehicle role (1 if struck by other vehicle, 0 otherwise)	1.522	17.311	0.000
The most harmful event (1 if rollover, 0 otherwise)	1.691	19.231	0.000
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	1.251	12.857	0.000
Standard Deviation of parameter distribution	*1.004*	*12.524*	*0.000*
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	2.617	11.868	0.000
Standard Deviation of parameter distribution	*3.119*	*18.117*	*0.000*
Vehicle maneuver just prior to impending crash (1 if going straight, 0 otherwise)	0.457	5.427	0.000
Factor of crash identified in the investigation (1 if speed, 0 otherwise)	-0.846	-7.868	0.000
Driver's attention level at the time of impending crash (1 if distraction or inattention, 0 otherwise)	-1.158	-7.733	0.000
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	-3.250	-17.810	0.000
Location of the occupants in the vehicle (1 if for passenger position, 0 otherwise)	1.018	5.533	0.000
Gender of the occupants (1 if male, 0 otherwise)	0.719	5.598	0.000
Standard Deviation of parameter distribution	*0.546*	*13.735*	*0.000*
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	-0.789	-7.864	0.000
Threshold 1, $\mu 1$	2.845	14.047	0.000
Threshold 2, $\mu 2$	4.708	21.307	0.000
Threshold 3, $\mu 3$	6.280	25.969	0.000
Log-likelihood at zero, LL(0)	-3258.341		
Log-likelihood at convergence, LL(β)	-3022.542		
Chi-squared value (χ^2)	471.598		
McFadden's pseudo, R^2	0.072		
Number of observations, N	6,588		

Table 6: Multi-Vehicle Mixed Logit Model Results

Injury Severity - Mixed Logit	Random Parameters Model		
	Coeff.	*t*-stat	*P*-value
Fatal Outcome			
Constant	-8.729	-4.047	0.000
Standard Deviation of parameter distribution	*2.663*	*2.618*	*0.009*
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	2.939	2.272	0.023
Light condition of street (1 if dark, 0 otherwise)	2.065	3.298	0.001
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	2.804	2.278	0.023
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	2.224	3.066	0.002
Incapacitating Injury Outcome			
Constant	-3.027	-14.942	0.000
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	1.279	2.550	0.018
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	2.276	2.927	0.003
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	-3.233	-1.956	0.051
Standard Deviation of parameter distribution	*2.195*	*2.126*	*0.033*
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	0.495	2.159	0.031
Time of the day (1 if 5 am in the morning, 0 otherwise)	1.235	4.381	0.000
Non-incapacitating Injury Outcome			
Constant	-8.233	-2.176	0.029
Standard Deviation of parameter distribution	*4.522*	*1.993*	*0.046*
Occupants' use of available vehicle restraints (1 if no restraint used,0 otherwise)	4.320	2.219	0.026
Time of the day (1 if 4 am in the morning, 0 otherwise)	2.119	1.831	0.067
Months of the year (1 if summer months (June to August), 0 otherwise)	0.852	1.756	0.079
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	-1.396	-1.816	0.069
Possible Injury Outcome			
Constant	-2.678	-10.091	0.000
Gender of the occupants (1 if male, 0 otherwise)	-0.455	-2.311	0.021
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.790	5.510	0.000
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	0.346	1.994	0.046
Number of vehicles involved in the crash	0.245	3.767	0.000
Road surface condition (1 if wet, 0 otherwise)	0.504	3.696	0.037
Non-Injury Outcome (Property-Damage-Only)			
Alignment of highway section (1 for curved section, 0 otherwise)	-0.339	-2.162	0.031
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	-0.232	-2.161	0.031
Light condition of street (1 if the surrounding area is dark but outside is lighted, 0 otherwise)	0.512	2.940	0.003
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.371	2.086	0.037
Driver's attention level at the time of pre-crash (1 if sleepy, 0 otherwise)	-2.188	-3.357	0.001
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.741	7.510	0.000
Log-likelihood at zero, LL(0)		-10602.98	
Log-likelihood at convergence, , LL(β)		-3081.050	
Chi-squared value (χ^2)		15043.85	
McFadden pseudo-R^2		0.709	
Number of observations, N		6,588	

The second parameter – rollover, having a mean of -3.233 and standard deviation of 2.195, has 92.9% of observations below zero. This fact indicates that 92.6% of multiple vehicle crashes associated with rollover resulted in a decrease in incapacitating injuries. The third parameter – constant specific to non-incapacitating injury, having a mean of -8.233 and standard deviation of 4.522, has 96.6% of observations below zero. This captures some unobserved heterogeneity present in the non-incapacitating injury category in the multiple vehicle large truck involved crashes.

Statistical goodness-of-fit of both discrete choice models are presented in Table 5, where the random parameter ordered probit model was first considered as base model and then mixed logit was estimated progressively from the base model. The reported pseudo-R^2 is 0.709 for the mixed logit model, in contrast to 0.072 for the random parameter ordered probit model, implying the mixed logit model fits the data better, predicting the multi-vehicle crashes for all five injury outcomes. It is clearly found that log-likelihood at convergence is much better for the mixed logit model over the random parameter ordered probit model. The Chi-squared values support the mixed logit model as well.

With regard to under reporting issues of less severe crashes compared to more severe crashes, the estimated model could lead to erroneous inferences (Savolainen et al. 2011; Washington et al. 2011). Model estimation, particularly for the ordered probit model, resulting from such data sample leads to non-randomness in its dependent variable with a violation of fundamentals of econometric model derivations (Savolainen et al. 2011). However, mixed logit accounts for limited data by considering a mixing distribution in the estimation process with a flexibility of varying the coefficient for each observation in the data sample (Gkritza and Mannering 2008).

Table 7: Model Results of Discrete Outcome Models

Items related to Goodness-of-fit	Mixed Logit Model	Random Parameter Ordered Probit Model
Number of observations	6,588	6,588
Restricted log-likelihood	-10602.980	-3258.341
Log-likelihood at convergence	-3081.050	-3022.542
Chi-squared value	15,043.85	471.598
McFadden Pseudo R^2	0.709	0.072
Number of random parameters	3	5
Number of parameters	31	24

Considering the better goodness-of-fit by the mixed logit model (Table 7), only the marginal effects in terms of average direct pseudo-elasticities were considered to be reported and computed to measure the impact of respective variables for the mixed logit model on the corresponding injury outcomes. The average direct pseudo-elasticities of the mixed logit model are presented in Table 8.[4]

Table 8: Marginal Effects of Multi-Vehicle Mixed Logit Model

Variables	Elasticity (%)				
	PDO/No Injury	Possible Injury	Non-incapac-itating	Incapacitating	Fatal
Human factors					
Gender of the occupants (1 if male, 0 otherwise)	2.33	-38.28	1.17	2.56	2.15
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	-0.16	-0.19	-0.10	7.75	-0.15
Driver's attention level at the time of impending crash (1 if sleepy, 0 otherwise)	-0.09	0.92	0.21	1.04	0.81
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	-0.78	12.80	-0.41	-0.92	-0.67
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	-0.22	3.67	-0.13	-0.31	-0.24
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	-0.42	-0.55	11.48	-0.63	-0.58
Road and Environmental Factors					
Light condition of street (1 if dark, 0 otherwise)	-0.23	-0.26	-0.13	-0.36	50.26
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	-0.14	-0.17	-0.08	-0.13	30.06
Time of the day (1 if 5 am in the morning, 0 otherwise)	-0.49	-0.54	-0.32	23.86	-0.83
Time of the day (1 if 4 am in the morning, 0 otherwise)	-0.13	-0.12	3.49	-0.33	-0.18
Months of year (1 if summer months (June to August), 0 otherwise)	-0.41	-0.48	10.96	-0.49	-0.40
Road surface condition (1 if wet, 0 otherwise)	-0.57	9.43	-0.29	-0.62	-0.55
Alignment of highway section (1 for curved section, 0 otherwise)	-0.31	2.99	1.14	2.41	2.44
Vehicular Factors					
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	-0.11	-0.11	-0.08	5.24	-0.11
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	4.39	-39.80	-20.37	-36.19	-35.30
Number of vehicles involved in the crash	-3.37	55.42	-1.72	-4.06	-3.05
Crash Mechanism					
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	-0.05	-0.07	-0.05	-0.12	12.15
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	-0.05	-0.06	-0.03	-0.04	11.47
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	-0.44	-0.66	-0.30	22.17	-0.46
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	-0.20	-0.10	-0.19	9.60	-0.13
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.47	0.41	-12.37	0.32	0.37
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.27	-2.57	-1.19	-1.99	-2.24

Human Factors

Male occupants are 38.3% less likely to be involved in possible injuries compared with females as supported in a study by Chen and Chen (2011) that male occupants are less likely to be involved in fatal or incapacitating and non-incapacitating or possible injuries[5]. Distracted driving is 7.7% more likely to result in incapacitating injuries because of multiple vehicular interactive dynamics. Not wearing a seatbelt results in 11.5% more likelihood to be involved in a crash with non-incapacitating injury outcomes. This might indicate the unbelted occupants to be involved in non-incapacitating injuries rather than drivers. Similar findings by Chen and Chen (2011) also indicated this is true for fatal or incapacitating and non-incapacitating or possible injuries. Drivers residing or registered to work in the state of Texas are 12.8% more likely to be involved with possible injuries. Sleepy drivers are more likely to be not involved with non-injury which indirectly shows them more likely to be involved with serious injuries. As found in the random parameter ordered probit model, the presence of passengers reduces the likelihood of severe injuries, which might indicate the passengers keep the drivers alert on long drives. Also, speeding as a factor of crashes increases the likelihood of possible injuries by 3.7%, although choice of driving speed might be also influenced by geometric features of the roadway segment and drivers' behavior. Geometric features may include number of travel lanes, vertical grade, inside and outside shoulder, horizontal curvatures, and rumble strips presence (Amarasingha and Dissanayake 2013). Thus, although the magnitude of the two studies in terms of variables are different due to different estimation methods, most of the explanatory variables have the same sign.

Road and Environmental Factors

Dark conditions lead to a 50.3% greater likelihood of fatalities since other vehicles might be completely blinded by such unfavorable driving conditions. This fact is supported with a similar study by Chen and Chen (2011) where dark condition increases both fatal or incapacitating injuries and non-incapacitating or possible injuries. Similarly, wet road surface increases possible injuries by 9.4%. Time of day and month of the year implies the traffic condition on the highway. Time of day is a significant factor. Driving at 2 pm increases the likelihood of fatalities by 30.1%, which may indicate that drowsy driving after lunch affects by vehicles other than trucks. Driving between 4 and 5 am increases the likelihood of a non-incapacitating injury crash by 3.5% and an incapacitating injury crash by 23.9%, respectively, which indicates sleepy or drowsy driving. Sleepy or fatigue driving could also lead to run-off-road crashes and result in severe injury crashes (Roy and Dissanayake 2011). Summer months (from June to August) increases the likelihood of non-incapacitating injury crashes by 11% because of more traffic on the highways and greater chances of interaction between vehicles leading to crashes. Wet pavement condition increases by 9.4% the likelihood of possible injuries because of unfavorable driving and braking on slippery road conditions for other vehicles and the braking characteristics of large trucks. Curved segments of the highways decrease the likelihood of non-injury crashes, which indirectly points toward serious injuries.

Vehicular Factors

Tire related malfunction increases the likelihood of incapacitating injury by 5.2%, which indicates the lack of vehicle maintenance of commercial vehicles resulted in weight imbalance and uncontrolled driving situations. This situation could lead to severe injuries if run-off-road crashes can be imminent of this tire malfunction. A study by Roy and Dissanayake (2011) indicated that tired-related factors can be very dangerous, resulting in run-off-road crashes. However, this fact is contradicted by a similar study by Chen and Chen (2011) where tire defects decrease the likelihood of f non-incapacitating injuries. A single trailing unit decreases the major injury categories (i.e.,

fatality, incapacitating injuries, non-incapacitating injuries, and possible injuries by 35.3%, 36.2%, 20.4%, and 39.8%, respectively).

Crash Mechanism

Departing the roadway (by left or right side of roadway) increases the likelihood of fatalities by 12.2%, which is also supported in a study by Chen and Chen (2011). Head-on collision also increases the likelihood of fatalities by 11.5%. This fact is supported by Chen and Chen (2011) through the variables such as driving on the wrong side or wrong way, which might indicate a head-on impact with oncoming vehicles. Vehicle rollover situations increase the likelihood of incapacitating injuries 9.6%, which are complex in nature for multi-vehicle crashes. This fact is contradicted by Chen and Chen (2011) findings on truck overturn crashes. Rear-end crashes increase the likelihood of incapacitating injuries by 22.2% and decreases the likelihood of non-injury crashes. Sideswipe in the same direction decreases the likelihood of non-incapacitating injuries by 12.4%. As the number of vehicles involved in multiple vehicle crashes increases, the likelihood of possible injuries increases by 55.4%, which is supported in a similar study by Chen and Chen (2011) that more than three vehicles involved in the collision increases fatal, incapacitating, non-incapacitating, or possible injuries. Speed-related factor, which is speeding for the existing driving condition, increases the likelihood of possible injuries, which is supported by the fact that exceeding the speed limit increases the likelihood of possible or non-incapacitating injuries in a study by Chen and Chen (2011). Lane changing behavior increases the likelihood of non-injury crashes (i.e., property-damage-only) which results from multi-vehicle interactions. As found in the random parameter ordered probit model, vehicles struck by other vehicles as consequences of vehicular interaction reduces the likelihood of severe injuries. Likewise, driving on the lane or going straight keeping the lane, which indicates no lane changing behavior, also reduces the likelihood of severe injuries.

CONCLUSION

Utilizing the nationwide GES crash database, two discrete outcome random parameter models were investigated. These models made it possible to minimize the possible bias and erroneous inferences by considering the estimated coefficients to vary across the crash observations (McFadden and Train 2000, Train 2009). The random parameter ordered probit model was used because of the ordinal characteristics of the injury scale (the KABCO scale was followed), and the mixed logit model used for methodological flexibility such as each injury outcome has individual utility functions and independent of irrelevant alternatives (IIA). The IIA property in the mixed logit model provides the flexibility of variables within each of the particular injury outcomes being independent on the utility function as well as between the outcomes (Jones and Hensher 2007). The random parameter ordered probit model provides the indication of more and less severe injury outcomes based on the sign of the variables. On the other hand, the mixed logit model characterizes more or less severe injury outcomes with individual injury outcome through utility function set-up. The results of both models are presented here (Table 3 and Table 4) as well as their statistical performance. The parameter estimates and statistical goodness-of-fit clearly indicate that mixed logit model is superior to random parameter ordered probit model. However, a tradeoff is made in model selection between ordered response variable in ordered probability models as opposed to unordered probability models (Washington et al. 2011).

Several crucial factors from the human aspect were identified in this study. Distracted and sleepy driving, male occupants (driver or passengers), drivers residing or working in the state of Texas, and not using a seatbelt are listed in the Empirical Results section as showing the increased risk of being seriously injured in a multi-vehicle collision with a large truck.

Road and environmental factors such as dark driving conditions and time of day can increase severe injuries. On the other hand, curved road segments and wet surface conditions only increase minor injuries. Vehicular factors such as tire related defects increase severe injury; whereas, single trailing unit such as semi-trailer involved in multi-vehicle crashes increases non-injury (i.e., PDO crashes) crashes.

Factors that are part of the human response are the maneuvers which are mainly executed by drivers at the impending or pre-crash situations. Actions such as departing roadway, rear-end collision, head-on collision, and vehicle rollover increases the severity of injuries. On the other hand, sideswipe (same direction), the number of vehicles involved in the crashes, speeding for the condition such as unfavorable weather or heavy traffic, increases minor injuries in multi-vehicle large truck crashes.

The variables that explained multi-vehicle crashes involving large trucks include human (i.e., sleepy driving), road and environmental factors (i.e., 2 pm, 4 to 5 am, wet surface, curved segments, dark but illuminated condition), vehicular factors (i.e., tire related defects), and crash mechanism (i.e., head-on and rear-end collision, number of vehicles involved in the crashes).

Although the GES dataset does not contain any traffic information (such as average annual daily traffic or vehicle-miles travelled), proxy variables such as time of day (2 pm, 4 to 5 am), and month of year (June to August) were considered in the mixed logit and random parameter ordered probit models to capture traffic conditions at the time of crash. It is worth investigating the contributing factors for single and multiple vehicle crashes involving large trucks and understand their role and differences in leading to large truck crashes on U.S. highways, for instance, an interstate facility. From the practical application of the models, the contributing factors related to human, such as distraction/inattention, driving speed, vehicular such as the tire related malfunction, and road-environment, such as light and surface condition, clearly indicate the importance of drivers' education and training as well as the installation of roadside lights and roadside warning signs on wet surfaces along the critical segments. Also, policy related decisions, including routine inspection of tires for the large trucks prior to long haul trips, should be implemented.

This study was conducted during the graduate study of the corresponding author at the University of Texas at El Paso during the period of 2010 to 2012.

Acknowledgements

The author sincerely thanks the co-general editor of JTRF, Dr. Michael Babcock, for his kind help, time, and invaluable comments and suggestions on improving the quality of the paper to a large extent.

Endnotes

1. If the database contains all the various function classes (i.e., interstates, arterials, collectors, and local streets) it is difficult to separate the effects of variables coming from different functional classes on injury outcomes. Thus, splitting the database containing only crashes on interstate highways will produce better parameter estimates and marginal effects on injury outcomes.

2. Analysis began with the same set of explanatory variables for both models. However, after model estimation, the mixed logit model had more statistically significant variables than the random parameter ordered probit model.

   Also, it is desirable to include traffic in the models but the GES database does not have AADT (annual average daily traffic).

3. Random parameter probit and mixed logit models capture the variation of the variables across the observations that influence the dependent variable, resulting in parameter heterogeneity.

4. Other variables such as speed limit at the crash locations, age of the drivers, and rural/urban nature of the crashes were not included. Speed limit is not in the GES database and age of the driver and rural/rural location could be correlated with other variables in the models. Further research involving these variables is planned.

5. Each observation in the sample is a crash with maximum injury levels of the occupants, which can be either the driver or passengers. In the case of multiple vehicle crashes, a vehicle with an occupant that sustained the maximum injury severity among all the occupants in the crash involved vehicles was considered in the model.

References

Abdel-Aty, M. "Analysis of Driver Injury Severity Levels at Multiple Locations Using Ordered Probit Models." *Journal of Safety Research* 34, (2003): 597–603.

Amarashinga, N. and S. Dissanyake. "Modeling Frequency of Truck Crashes on Limited-Access Highways." *Journal of Transportation Research Forum* 52(3), (2013): 123-139.

Anastasopoulos, P.Ch. and F.L. Mannering. "A Note on Modeling Vehicle-Accident Frequencies with Random Parameter Count Models." *Accident Analysis and Prevention* 41(1), (2009):153-159.

Anastasopoulos, P., Ch. and F.L. Mannering. "An Empirical Assessment of Fixed and Random Parameter Logit Models Using Crash- and Non-Crash-Specific Injury Data." *Accident Analysis and Prevention* 43(3), (2010): 1140–1147.

Bhat, C. "Quasi–random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model." *Transportation Research Part B* 17(1), (2001): 677-693.

Bhat, C. "Simulation Estimation of Mixed Discrete Choice Models Using Randomized and Scrambled Halton Sequences." *Transportation Research Part B* 37(1), (2003): 837-855.

Brownstone, D. and K. Train. "Forecasting New Product Penetration with Flexible Substitution Patterns." *Econometrica* 89, (1999): 109-129.

Chen, F. and S. Chen. "Injury Severities of Truck Drivers in Single- and Multiple-Vehicle Accidents on Rural Highways." *Accident Analysis and Prevention* 43(5), (2011): 1677-1688.

Chistoforou, Z., S. Cohen, and M.G. Karlaftis. "Vehicle Occupant Injury Severity on Highways: An Empirical Investigation." *Accident Analysis and Prevention* 42(6), (2010): 1606 –1620.

Geweke, J., M. Keane, and D. Runkle, "Alternative Computational Approaches to Inference in the Multinomial Probit Model." *The Review of Economics and Statistics* 76(4), (1994): 609-632.

Geedipally, S.R. and D. Lord. "Investigating the Effect of Modeling Single-vehicle and Multiple Vehicle Crashes Separately on Confidence Intervals of Poisson–gamma Models." *Accident Analysis and Prevention* 42(4), (2010): 1273–1282.

Greene, W. *Limdep, Version 9.0*. Econometric Software, Inc., Plainview, New York, 2007.

Gray, R.C., M.A. Quddus, and A. Evans. "Injury Severity Analysis of Accidents Involving Young Male Drivers in Great Britain." *Journal of Safety Research* 39(5), (2008): 483–495.

Gkritza, K. and F.L. Mannering. "Mixed Logit Analysis of Safety-belt Use in Single- and Multi-Occupant Vehicles." *Accident Analysis and Prevention* 40(2), (2008): 443-451.

Halton, J. "On the Efficiency of Certain Quasi-Random Sequences of Points in Evaluating Multi-Dimensional Integrals." *Numerische Mathematik* 2, (1960): 84–90.

Insurance Institute for Highway Safety (IIHS), Highway Safety Research and Communications. Available online at http://www.iihs.org/research/fatality_facts_2009/largetrucks.html.

Islam, M.B. and S. Hernandez. "Large Truck Involved Crashes: An Exploratory Injury Severity Analysis." *Preprint CD-ROM of the 91st Annual Meeting of Transportation Research Board*, Washington D.C., 2012.

Islam, M.B. and S. Hernandez. "An Empirical Analysis of Fatality Rates for Large Truck Involved Crashes on Interstate Highways." *3rd International Road Safety and Simulation*, Indianapolis, 2011.

Ivan, J.N., R.K. Pasupathy, and P.J. Ossenbruggen. "Differences in Causality Factors for Single and Multiple Vehicle Crashes on Two-lane Roads." *Accident Analysis and Prevention* 31(6), (1999): 695–704.

Ivan, J.N., C. Wang, and N.R. Bernardo. "Explaining Two-lane Highway Crash Rates Using Land Use and Hourly Exposure." *Accident Analysis and Prevention* 32(6), (2000): 787–795.

Jones, S. and D. Hensher. "Evaluating the Behavioral Performance of Alternative Logit Models: An Application to Corporate Takeovers Research." *Journal of Business Finance Accounting* 34, (2007): 1193–1220.

Jung, S., X. Qin, and D.A. Noyce. "Injury Severity of Multivehicle Crash in Rainy Weather." *Journal of Transportation Engineering* 138(50), (2012): 50–59.

Kim, J.K., G. Ulfarsson, V. Shankar, and F.L. Mannering. "A Note on Modeling Pedestrian Injury Severity in Motor Vehicle Crashes with the Mixed Logit Model." *Accident Analysis and Prevention* 42(6), (2010): 1751–1758.

Kockelman, K.M. and Y.J. Kweon. "Driver Injury Severity: An Application of Ordered Probit Models," *Accident Analysis and Prevention* 34(3), (2002): 313–321.

Lemp, J. D., K.M. Kockelman, and A. Unnikrishnan. "Analysis of Large Truck Crash Severity Using Heteroskedastic Ordered Probit Models." *Accident Analysis and Prevention 43 (1),* (2011): 370-380.

Lee, C. and M. Abdel-Aty. "Comprehensive Analysis of Vehicle–Pedestrian Crashes at Intersections in Florida." *Accident Analysis and Prevention* 37(4), (2005): 775–786.

Lee, L. "On Efficiency of Method of Simulated Moments and Maximum Simulated Maximum Estimation of Discrete Response Models." *Econometric Theory* 8(3), (1992): 518–552.

Limdep, *NLOGIT Version 4.0*, Econometric Software, Planeview, NY, 2007.

McKelvey, R.D. and W. Zavoina. "A Statistical Model for Analysis of Ordinal Level Dependent Variables." *Journal of Mathematical Sociology* 4(1), (1975): 103–120.

McFadden, D. and K. Train. "Mixed MNL Models for Discrete Response." *Journal of Applied Econometrics* 15, (2000): 447-470.

McFadden, D. "Econometric Models of Probabilistic Choice." D. Manski and D. McFadden (eds.), *A Structural Analysis of Discrete Data with Econometric Applications*. The MIT Press, Cambridge, MA, 1981.

McFadden, D. and P. Ruud. "Estimation by Simulation," *The Review of Economics and Statistics* 76(4), (1994): 591-608.

Milton, J.C., V.N. Shanker, and F.L. Mannering. "Highway Accident Severities and the Mixed Logit Model: An Exploratory Empirical Analysis." *Accident Analysis and Prevention* 40(1), (2008): 260-266.

National Automotive Sampling System (NASS) General Estimates System (GES). *Analytical User's Manual 1988-2010*. http://www-nrd.nhtsa.dot.gov/Pubs/AUM08.pdf, 2008.

National Highway Traffic Safety Administration (NHTSA). *Traffic Safety Facts 2009: Large Trucks*. DOT HS 811 388. Available online at http://www-nrd.nhtsa.dot.gov/Pubs/811388.pdf, 2011.

National Cooperative Highway Research Program. *Report 500*, *Volume 13: A Guide for Reducing Collision Involving Heavy Trucks*, 2004. http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_500v13.pdf

O'Donnell, C.J. and D.H. Connor. "Predicting the Severity Using Models of Ordered Multiple Choice," *Accident Analysis and Prevention* 28(6), (1996): 739–753.

Pai, C.W. and W. Saleh. "Modelling Motorcyclist Injury Severity by Various Crash Types at T-Junctions in the UK." *Journal of Safety Science* 46(8), (2008): 1234–1247.

Quddus, M.A., R.B. Noland, and H. Chor Chin. "An Analysis of Motorcycle Injury and Vehicle Damage Using Ordered Probit Models." *Journal of Safety Research* 33(4), (2002): 445–462.

Revelt, D. and K. Train. "Mixed Logit with Repeated Choices: Households' Choice of Appliance Efficiency Level." *Review of Economics and Statistics* 80(4), (1997): 647-657.

Revelt, D. and K. Train. "Customer Specific Taste Parameters and Mixed Logit." Working Paper, University of California, Berkeley, Department of Economics (1999).

Roy, U. and S. Dissanyake. "Comparison of Factors Associated with Run-Off-Road and Non-Run-Off Road Crashes in Kansas." *Journal of Transportation Research Forum* 50(2), (2011): 69-86.

Stern, S. "Simulation-based Estimation." *Journal of Economic Literature* 35(4), (1997): 2006-2039.

Statistical Analysis System, *SAS® 9.2 for Windows*. SAS Institute, Inc., Cary, NC.

Savolainen, P.T. and F.L. Mannering. "Probabilistic Models of Motorcyclist' Injury Severities in Single- and Multi-vehicle Crashes." *Accident Analysis and Prevention* 39(5), (2007): 955-963.

Savolainen, P.T., F.L. Mannering, D. Lord and M.A. Quddus. "The Statistical Analysis of Highway Crash-injury Severities: A Review and Assessment of Methodological Alternatives." *Accident Analysis and Prevention* 43(5), (2011): 1666– 1676.

Train, K. "Mixed Logit Models for Recreation Demand." C. Kling and J. Herriges (eds.), *Valuing the Environment Using Recreation Demand Models*. Elgar Press, NY, 1997.

Train, K. "Halton Sequences for Mixed Logit." Working Paper, University of California Berkley, Department of Economics. 1999.

Train, K. *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge, UK. 2003.

Train, K. *Discrete Choice Methods with Simulation*. Cambridge University Press, NY, 2009.

Viano, D.C., C.C. Culver, L. Evans and M. Frick. "Involvement of Older Drivers in Multivehicle Side-impact Crashes." *Accident Analysis and Prevention* 22(2), (1990): 177-188.

Walker, J. and M. Ben-Akiva, "Generalized Random Utility Model." *Mathematical Social Sciences* 43(3), (2002): 303–343.

Washington, S.P., M.G. Karlaftis, and F.L. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis*, 2nd Ed. Chapman & Hall/CRC, Boca Raton, FL, 2011.

Xie, Y., Y. Zhang, and F. Liang. "Crash Injury Severity Analysis Using Bayesian Ordered Probit Models." *Journal of Transportation Engineering* 135(1), (2009): 18-25.

Ye, F. and D. Lord. "Investigating the Effects of Underreporting of Crash Data on Three Commonly Used Traffic Crash Severity Models: Multinomial Logit, Ordered Probit and Mixed Logit Models," *Preprint CD-ROM of the 90th Annual Meeting of Transportation Research Board*, (2011), Washington D.C., 2011.

Zhu, X. and S. Srinivasan. "A Comprehensive Analysis of Factors Influencing the Injury Severity of Large-Truck Crashes." *Accident Analysis and Prevention* 43(1), (2011): 49-57.

Zajac, S. and J.N. Ivan. "Factors Influencing Injury Severity of Motor Vehicle-Crossing Pedestrian Crashes in Rural Connecticut." *Accident Analysis and Prevention* 35(3), (2002): 369–379.

Mouyid Islam *is a highway safety engineer at CH2M HILL, Inc. He received his Ph.D. from the University of Texas (El Paso), M.Sc. from Purdue University, and B.Sc. (Civil Engr.) from Bangladesh University of Engineering and Technology. Mouyid's work and interest focuses on highway safety highlighting predictive safety analysis (Highway Safety Manual), systemic safety analysis, statistical analysis and modeling. He is involved with the Institute of Transportation Engineers, American Society of Civil Engineers, and Transportation Research Board's safety committees.*

Review, Experimental Evaluation and Policy Considerations of a Directional Time of Day Truck Restriction on Highways

by Shy Bassan

The paper reviews several strategies of restricting or separating trucks from the regular traffic stream. Typical truck restriction policies focus on leftmost lanes restriction, which has been shown by several studies to have some advantages. However, those studies clearly show that vehicle queue lengths in the vicinity of critical merging areas increase significantly as the percentage of trucks increases. Therefore, this study examines a different policy—one which investigates traffic efficiency gained by restricting heavy truck traffic in one direction—in this case, westbound on Highway 1 in Israel—during afternoon peak hours. Similar policies of utilizing a specific vehicle category (e.g. passenger cars or trucks) in different daily time periods or physical separation of homogenous traffic of passenger cars in the inner lanes and mixed traffic in the outer lanes, were recommended in Italian motorways and in New Jersey Turnpike dual-dual freeways respectively.

Highway 1 is a freeway connecting Jerusalem and Tel Aviv that passes by Ben-Gurion International Airport. The major objective of this study is to estimate the benefit of restricting truck traffic in the traffic stream according to three traffic-flow parameters: average travel time, total travel time, and average traffic speed. Analysis of the results, which consider the significant differences of 30-minute time period samples ("before-after" truck restriction), shows that prohibiting trucks in all lanes in one direction during the peak afternoon period of 16:00-18:00 improved all three traffic flow parameters by 8%-12%. Generally a steep grade from which truck traffic is banned is correlated with an improvement in traffic flow. In our case, Highway 1 road segments 1 and 2 and 4, which have steep grades (longitudinal grades), incorporated the most significant improvements in the traffic stream parameters examined.

INTRODUCTION

The large presence of trucks (especially slow trucks) on interurban highways increases the variability of the traffic flow, because of the differences in operational characteristics between the heavy vehicles and passenger cars. Trucks have a lower capability to accelerate or to harmonize with the speed of the general traffic, particularly on steep and continuous grades in the road profile (longitudinal grades). Therefore, trucks may cause the formation of long queues; merging, diverging (Siuhi and Mussa 2007, El Tantawy et al. 2009), and weaving difficulties; and a deterioration in both traffic flow quality and traffic capacity.

As far as safety is concerned, the presence of trucks in the traffic stream reduces sight distance while the travel changes direction (therefore it requires driving along curves) and while the steepness of grade changes its magnitude and trend (either from upgrade to downgrade or from moderate grade to steeper grade and vice versa). Such driving maneuvers have to be taken into account in the design of horizontal and vertical curves along the highway alignment correspondingly, as clarified in Appendix A. Sight distance reduction (by the presence of trucks in the traffic stream) might hide the viewing of traffic and message signs as well.

When passenger car drivers want to pass wider trucks, they might position themselves too close to the pavement edge and so reduce the margin of safety. Furthermore, trucks traveling at high speed create significant air disturbances, which can cause unsuspecting motorists to lose control of their cars. Large trucks also exert psychological effects. Passenger car drivers often feel threatened by the

closeness of trucks in an adjacent lane, since the large vehicles occupy more length and lane width than does a passenger car.

Implementing truck restrictions may enhance the efficiency of highway travel through reducing the travel times of regular traffic and improving safety; however, trucking companies have expressed concern over such steps, since such restrictions can negatively impact trucks' travel times and change their travel routes and scheduling. Therefore, the profitability and efficiency of these trucking companies might diminish. Deterioration in profitability and efficiency of trucking companies by denying access to trucks also impacts the economic efficiency of industries and variety of producers.

This study focuses on an investigation of traffic efficiency when heavy truck traffic is restricted. The case study for this investigation was Highway 1 in Israel during afternoon peak hours. Route 1 is a major highway that connects the cities of Jerusalem and Tel Aviv and passes through the Ben-Gurion International Airport interchange. The highway section examined transfers of nearly 3,000 vehicles per hour in each direction exiting/entering Jerusalem; about 5% of this traffic comprises trucks (approximately 150 trucks per hour in each direction). This section starts at the Sakharov Gardens intersection (exiting Jerusalem) and ends at the Daniel Interchange (providing a merger to a freeway, Route 6). The section terrain is partially hilly and includes several horizontal and vertical curves. Its length is 34 kilometers. Heavy traffic conditions characterize the morning peak when driving eastward to enter Jerusalem and the afternoon peak hours when driving westward exiting Jerusalem. Delays are principally caused by heavy traffic, exacerbated by trucks slowing considerably on the upgrades of the hilly topography. Since there is no climbing lane, the regular traffic needs to perform a passing maneuver along the left lane, in effect leaving only one lane for the regular traffic stream when a slowing truck approaches the traffic stream. The major objective of this study is to estimate the benefits of restricting truck traffic on this section during the peak hours.

Research Motivation

Although a large amount of travel time and speed analyses (literature review section) had indicated that the left-most lanes from which trucks are restricted have some advantage compared to non-restricted lanes, the potential of vehicle queue length in the vicinity of critical merging areas increases significantly as the percentage of trucks increases. This phenomenon is associated with the unavailability of acceptable gaps for merging onto the freeway during peak traffic conditions and, consequently, with vehicular conflicts and the possibility of traffic crashes. This correlation and hardly any previous empirical and experimental studies of time of day truck restriction lead to the present study of prohibiting trucks from all lanes during peak hours.

The advantage of the procedure proposed in the current study is the analysis of average travel time and average speed parameters of a specific segment by direct measurements compared to the need for several steps to obtain these parameters according to HCM procedure.

LITERATURE REVIEW

In Germany, most trucks are limited to 80 or mostly 90 per km/hour (50 and 56 mph, respectively) on the "Autobahn" or freeway (expressway). The speed limit for cars and motorcycles is much higher: 130 km/hour (or 81 mph). This difference in speed limit between heavy vehicles and passenger cars is acceptable in European Union countries. The fact that traffic laws in Europe enforce drivers to keep driving on the right lane, excluding overtaking maneuvers, and that many expressways of the European highway network consist of two lanes per direction, lead to the practical outcome of restricting truck traffic to the right lane even though heavy vehicles are officially informed to drive on the right lane (McCarthy 2005).

Most of the traffic studies regarding the benefits of truck restrictions were performed in the United States. In general, trucks are restricted to using the rightmost lane or lanes of freeways because the left lanes are regarded as passing lanes. Nonetheless, there are some situations in which

trucks are restricted from using the right lanes instead of the left lane because of safety problems presented by merging and diverging traffic (Hoel and Peek 1999).

The major motivation of implementing lane restriction for trucks is improving traffic operation. Other incentives of implementing lane restriction for trucks are reducing vehicle crashes and limiting pavement damage (Yang and Regan 2013).

Prohibiting trucks from using certain lanes on multi-lane highways gives other vehicles the opportunity to enter the traffic stream and, avoiding the interference of heavy trucks, to reach a higher travel speed on the otherwise restricted lanes. This effect might improve the quality of traffic stream and increase a highway's capacity.

Strategies of Separating Cars from Trucks

Ferrari (2009, 2011) proposed a model of competition between cars and trucks on Italian motorways' sections when the willingness to use the motorway of both cars and trucks increased but the geometric characteristics remained unchanged. The fact that weekends and holidays are associated with almost only passenger car travel (one vehicle category) and weekdays include traveling by both categories and a progressive increase of truck traffic on motorways might suggest that motorways should be used by a specific vehicle category (e.g., one category: passenger cars or trucks) in different daily time periods (Ferrai 2009, 2011). Moreover, the strategy of separating cars and trucks on the New Jersey Turnpike dual-dual freeway also resulted in a safety improvement based on Lord et al. (2005).

Time-of-day restrictions are applied to prevent trucks from using a lane or a road during high-level traffic congestion. Some U.S. states restrict trucks from using a freeway in order to reduce peak traffic and increase travel speeds (Mussa 2004). Stokes and McCasland (1986) stated that truck traffic volume does not tend to peak during the regular morning and afternoon commuter peaks. Therefore, truck restriction during the regular driving peak hours could produce only subsidiary improvement in freeway traffic operations. Another interpretation is that prohibiting trucks during the peak hours of high travel demand might bring additional daily traffic to the traffic stream, causing operational improvement to the traffic flow to be marginal. Grenzeback et al. (1990) similarly found that the volume of large trucks on urban freeways does not have a crucial effect on the traffic stream during peak congestion hours unless either the percentage of truck traffic exceeds 10% or the congestion is accompanied by a truck incident, particularly a "truck-involved" accident.

Flow, Speed, Travel Time and Traffic Operations Studies

Jo et al. (2003) used VISSIM simulation software to assess the impact of prohibiting trucks from using the leftmost lanes on highways with 3-5 lanes in each direction. The study found that Truck Lane Restriction (TLR) increased throughput only when the restricted number of lanes was limited and the percentage of trucks was lower than 25%. The average speed increased under such conditions. The average speed was reduced, however, under high truck percentages and an increased number of restricted lanes; ramp volume and interchange density in this case had a negative effect on speed. The researchers recommended restricting trucks from the two leftmost lanes for rural area highways with 4-5 lanes in each direction and from the leftmost lane when there were three lanes in each direction. They recommended that truck lane restrictions should not be applied in urban areas, where capacity was critical.

Moses et al. (2007) simulated traffic flow of Interstate 95 in southern Florida They found that the restrictions of the right and center lanes caused traffic flow disruptions owing to the queues that developed upstream of interchanges during the peak hours; i.e., the formation of excessive queues as entering trucks waited long periods for a gap in order to move from the restricted lanes. Yang and Regan (2013) examined three truck traffic strategies for Interstate 710 (23-mile corridor in California): 1) no strategy for trucks, 2) trucks' restriction from one leftmost lane, and 3) trucks' restriction from two leftmost lanes. The analysis period was midday peak time (i.e., time of day) while traffic flow ranged between 970 and 1,950 vehicle/hour/lane with 13% trucks (annual basis).

A simulation analysis of 60 minutes resulted in minor improvement of traffic delay (minute per vehicle) along the corridor: 11.88 minutes per vehicle for strategy 1 (existing situation), 11.79 for strategy 2 (one leftmost lane restricted), and 11.55 for strategy 3 (two leftmost lanes restricted). This measure of effectiveness, which represented traffic congestion, decreased by only 2.8% if strategy 3 was implemented (Yang and Regan 2013). These results imply that in order to significantly improve traffic congestion it might be more reasonable to implement a directional time of day truck restriction strategy as proposed in the current study.

Siuhi and Mussa (2007) found that during peak hours, HOV lanes and car lanes experienced better travel times than did the lanes that permitted truck traffic. The leftmost lanes (including HOV lanes, which were restricted from trucks) had higher speeds than unrestricted lanes. They interpreted this by the fact that congestion on the right lanes ("queue length in the vicinity of critical merging and diverging areas") forces passenger cars to use the left lanes and concluded that restriction of HOV lanes and left lanes in urban freeways improves traffic operation and traffic safety during congested conditions rather than during non-peak traffic conditions. However, Mussa (2004) has shown that regardless of the time of day, no significant difference in travel time and travel delay occurred between restricted and unrestricted conditions (on Interstate 75, Florida).

Qi et al. (2009) investigated the restriction of trucks to the right lane of four-lane rural freeway (elevated I10, Louisiana) with a speed limit policy of 55 mph. Their statistical analysis indicated that the speed in the left lane was much higher than the speed in the right lane.

El-Tantawy et al. (2009) found that restricting the two leftmost lanes from trucks in Gardiner expressway (downtown Toronto) caused an increase in truck-related merging conflicts along the right lane.

Grade Effect

Using Remote Traffic Microwave Sensors (RTMS) technology to collect real traffic data, Cate and Urbanik (2004) investigated the impact of left-lane restriction in Knoxville, Tennessee (Interstates 40, 75). The scenarios were run for three lanes in each direction, with and without ramps. In order to quantify the effect of lane restriction, they conducted a before-and-after study. Travel time estimations showed that with an increased grade (4%), a left-lane truck prohibition resulted in saving travel time for PCs (passenger cars) and in slightly increasing travel time for trucks. However, the travel time savings for passenger cars on level terrain was minimal. Specifically, the speed differential between trucks and PCs was less than 1.0 mph on level terrain and approximately 10.0 mph on 4% upgrades. Furthermore, the average travel times for cars traveling a five-mile stretch along a freeway segment with a 4% uphill grade was reduced by approximately 60 seconds (Cate and Urbanik 2004).

Based on several literature sources, the overall impact of a left-lane restriction for trucks (or a limited number of restricting lanes from the left, e.g., two left lanes restricted out of for four or more lanes per direction) and directing the truck traffic to the rightmost lane moderately reduces the travel time of passenger cars in the restricted lanes where trucks are prohibited. However, some other studies might argue with this statement by either suggesting a physical separation between homogenous traffic of light vehicles and mixed traffic, and diverting trucks to alternative routes, or prohibiting trucks from the rightmost lanes to avoid merging and diverging impedance. Safety studies basically document reduction in crashes while prohibiting trucks from the left lane or physically separating the passenger car only lanes.

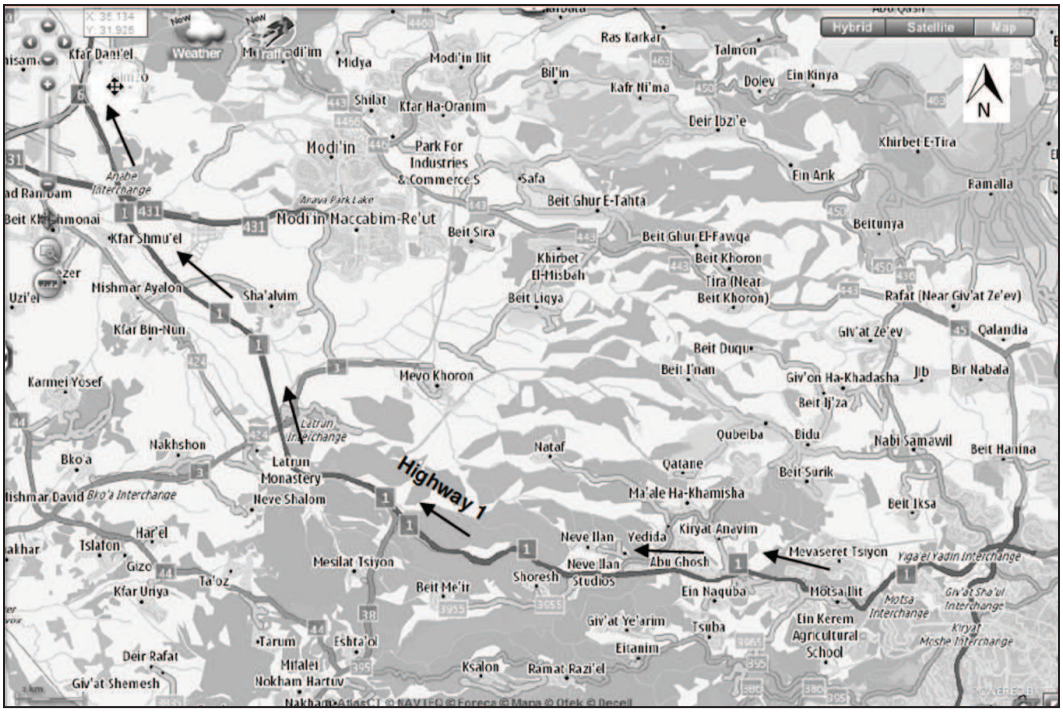
DATA FOR ANALYSIS AND PILOT STUDY DESCRIPTION

The pilot study examined traffic flow parameters before and after truck restrictions, based on two sets of measurements. The first data set was generated before the prohibition. The second data set was measured two months after applying the truck prohibition (beginning of March 2011) in order to maintain a "learning" period for the drivers to become accustomed to the new traffic regulations.

The data used for the analysis were obtained by restricting trucks in the westbound direction of Highway 1 during the peak afternoon hours, 16:00-18:00 (4-6 pm).

A traffic sign arrangement plan was implemented by posting signs announcing the prohibition of heavy trucks (above 12 tons) before the restricted segments and along the interchange ramps and the adjacent roads leading to these segments. Messages were also reported in the media in order to allow drivers and trucking companies to plan truck routes accordingly. During the pilot study, the police increased its enforcement along and prior to the prohibited zones. The restricted section along Highway 1 is presented in Figure 1.

Figure 1: Restricted Sections for Trucks Along Highway 1 Westbound from the Jerusalem Exit (from Sakharov Gardens Intersection – Daniel Interchange)



METHODOLOGY

The success of implementing the truck prohibition was evaluated by three traffic parameters:

(1) Average travel time (ATT); it was hypothesized that truck ATT would decrease by 5% or more compared with the ATT before the truck prohibition. The ATT for one subsection (ATT_k) is calculated as follows:

$$(1)\quad ATT_{k,j} = \left(\frac{\sum_{i=1}^{4}(Vol_{i,j} \bullet TT_{i,j})}{\sum_{i=1}^{4}(Vol_{i,j})}\right)$$

$$(2)\quad VOL_{k,j} = \sum_{i=1}^{4}(Vol_{i,j})$$

(3) $$ATT_k = \left(\frac{\sum_{j=1}^{3}(ATT_{k,j} \bullet VOL_{k,j})}{\sum_{i=1}^{3}(Vol_{k,j})}\right)$$

Where:

Vol_{ij} – traffic volume of one vehicle type (j) measured for half an hour (i) during the truck restriction period (16:00-18:00).

TT_{ij} – travel time of one vehicle type measured for half an hour during the truck restriction period (16:00-18:00)

i – 30-minute period sequence number during the afternoon peak hours (16:00-18:00), i.e. i=1 for the period 16:00-16:30, i=2 for the period 16:30-17:00, and so forth.

j – vehicle type (1 for light vehicles, 2 for medium vehicles, 3 for heavy vehicles)

k – segment (subsection) number

The ATT is calculated by summing up the ATT_k for all segments.

(2) The total travel time (TTT) after the truck prohibition was hypothesized to decrease by 5% or more than the TTT before the truck prohibition. The TTT is calculated by adding the product of the average travel time to the traffic volume of all traffic streams in each direction.

The TTT for one subsection (TTT_k) is calculated as follows:

(4) $$TTT_k = \sum_{j=1}^{3}\sum_{i=1}^{4}(Vol_{i,j} \bullet TT_{i,j})$$

The definitions of Vol_{ij}, TT_{ij}, j, and k are identical to the ATT_k equation. The TTT is calculated by summing up the TTT_k of all subsections.

ATT and TTT were calculated for the two-hour restriction period (16:00-18:00) before the truck restriction and after the restriction.

(3) The average speed (S) during the peak hour (16:30-17:30) of the restriction period was hypothesized to increase by 5% or more compared with the average speed before the truck prohibition. The average speed for one subsection (S_k) is as follows:

(5) $$S_k = \frac{L_k}{ATT_k},$$

Where:

ATT_K – calculated sum for two periods of 30 minutes each (during the peak hour period; i.e., a one-hour restriction period). Mathematically the summation is performed for i=2,3 in equations 1 and 2.

L_k – length of subsection k

The computed average speed for the whole section (S) is proportional to the length of the segment (L_k):

$$(6)\quad S = \frac{\sum_{k=1}^{8} S_k \bullet L_k}{\sum_{k=1}^{8} L_k}$$

Data for Analysis

Traffic counts and travel time measurements were collected during weekdays. The first data set before the prohibition of truck travel was measured on December 28, 2010. The second set (after the prohibition was applied) was measured on March 1, 2011. Both days of measurement are considered typical working days in Israel (no vacation and regular school days).

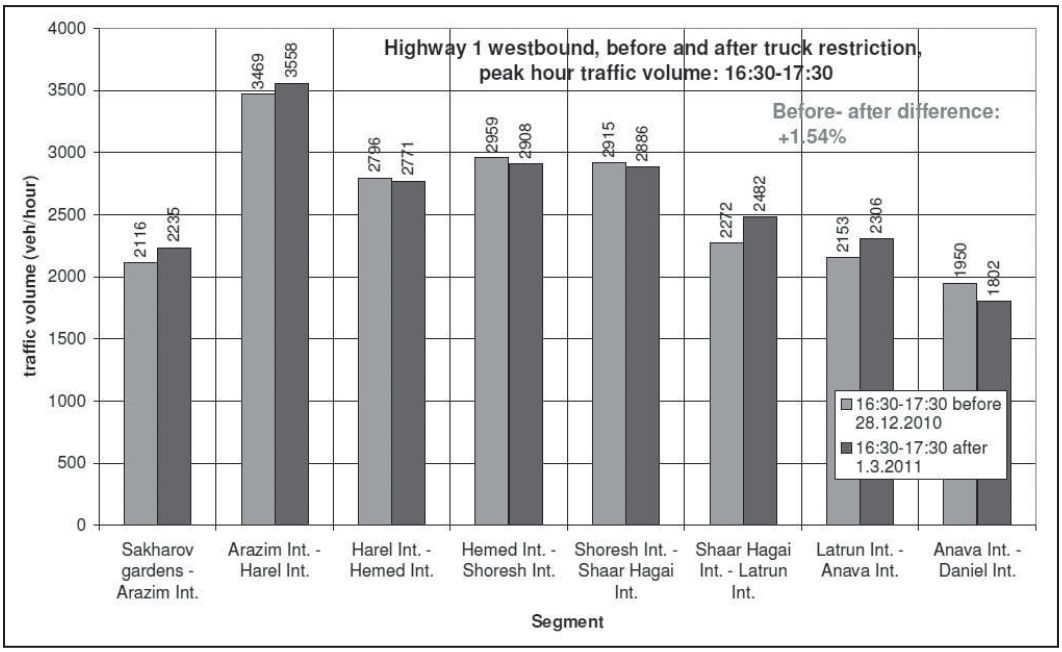
Division into Subsections. The entire study section along Highway 1 from the Jerusalem exit (Sakharov Gardens Intersection) to Highway 6 (Daniel Interchange) was divided into eight segments, based on ramp locations. Traffic flow parameters were measured on each segment. The partition points along the study section were at nine interchanges: Arazim, Harel, Hemed, Shoresh, Shaar Hagai, Latrun, Anava, and Daniel.

Vehicle Type. Three vehicle types were considered: light, medium, and heavy vehicles, with light vehicles corresponding to passenger cars, and medium vehicles to trucks with one rear axle. The medium vehicle type (mostly single unit trucks) could weigh either less or more than 12 tons. Heavy vehicles corresponded to buses, trucks with at least two rear axles, semi-trailers, and full trailers. Specific heavy trucks weighing more than 12 tons, which are considered vital by Israel's Ministry of Transport (e.g., trucks transporting basic food products, garbage trucks), received permission to drive along the prohibited routes. Buses, which are included in the heavy-vehicle category and are considered vital to the transportation system during the peak period, were not regarded as prohibited vehicles.

Traffic Counts. The raw data were collected by real-time video photography. Automatic vehicle counters were also used for backup and validation of the video traffic volume data.

Traffic counts were processed for each subsection for time periods of 30 minutes during the afternoon peak hours. Figure 2 presents a histogram of traffic volumes for the peak hour (16:30-17:30) before and after the truck-restriction period.

Figure 2: Traffic Volumes for Peak Hour (16:30-17:30) Before and After Truck Restriction



The volume of light vehicles increased by 2.35%, and the medium plus heavy vehicles decreased by 9.1%. The total number of vehicles increased by 1.54%. It appears, then, that the truck prohibition affected passenger car travels during the afternoon peak hour positively, but only slightly.

Travel Time Measurements. Travel times were measured from the raw data of the video recording of each segment by processing approximately 30 vehicles each half hour after the raw data results of the video recording of each segment were processed. Vehicle characteristics (light, medium, or heavy) were identified at the beginning and at the end of the segment in order to measure the travel time of each vehicle type that passed along the segment. The selection of vehicles for identification was random and approximately balanced between vehicle types in order to reflect all vehicle types in the traffic stream and preclude a bias in the estimated averages. The travel time was averaged according to vehicle type and each 30-minute period.

DATA ANALYSIS AND RESULTS

Before-After Statistical Analysis of Travel Time Measurements

Each sample of the before-and-after truck prohibition included the travel time (TT) segment measurements for one vehicle type (light, medium, or heavy). Two sample t-tests were made to examine whether the difference in the TT means (ATT) between the two samples (before and after the prohibition) was significant. The test assumed that the sample size was small ($n \leq 30$) and the standard deviations of the two populations were unequal (Satterhwaite's approximation, 1946). The H_0 and H_A hypothesis definitions are as follows:

H_0 (Null hypothesis): The means of two samples are not significantly different from each other.

H_A: The means of two samples are significantly different from each other (two-tailed t- test).

If the difference is not significant at the 5% significance level (95% confidence level), the ATT (average travel time) before and after the truck prohibition would be assumed to be identical (not significantly different) and computed as the "before and after" average travel time.

The equations required for testing the significance of the two samples are as follows:

$$t(actual) = \frac{ATT_a - ATT_b}{\sqrt{\left(\frac{s_a^2}{n_a} + \frac{s_b^2}{n_b}\right)}} \tag{7}$$

$$d.f. = \frac{\left(\frac{s_a^2}{n_a} + \frac{s_b^2}{n_b}\right)^2}{\frac{\left(\frac{s_a^2}{n_a}\right)^2}{n_a - 1} + \frac{\left(\frac{s_b^2}{n_b}\right)^2}{n_b - 1}} \tag{8}$$

Where:

s_a^2 – an estimate of the population variance (sample variance) after the truck prohibition (light, medium, or heavy vehicle) for a 30-minute time period

s_b^2 – an estimate of the population variance (sample variance) before the truck prohibition (light, medium, or heavy vehicle) for a 30-minute time period

n_a – sample size after the truck prohibition (light, medium, or heavy vehicle) at 30-minute time intervals

n_b – sample size before the truck prohibition (light, medium, or heavy vehicle) at 30-minute time intervals.

ATTa – sample mean after truck prohibition

ATTb – sample mean before truck prohibition

t(actual) – testing parameter: reject the null hypothesis ($ATT_a - ATT_b = 0$) if t(actual) exceeds $t_{0.05/2}$ or is less than $- t_{0.05/2}$

d.f. – calculated degrees of freedom, assuming unequal variances, based on the Welch–Satterthwaite approximation (Satterthwaite 1946, Welch 1947).

If t(actual) > $t_{0.05/2}$ (i.e., p-value ≤ 0.05), there is significant statistical evidence in support of rejecting the null hypothesis. In other words, the means of the two samples are significantly different. There is, in that event, no more than a 5% probability that we could obtain this result by chance (an acceptable level of error).

Typical Travel Time "Before-After" Analysis Examples for the Arazim Harel Segment

Table 1 presents a "before-after" analysis of two 30-minute periods during the afternoon peak hours on the Arazim Interchange–Harel Interchange road segment: 17:00-17:30. Table 2 summarizes the t-test travel time results for the whole afternoon peak period (16:00-18:00) for the Arazim–Harel

segment, based on four samples of 30-minute time periods (16:00-16:30, 16:30-17:00, 17:00-17:30, and 17:30-18:00) and vehicle type (light, medium, and heavy).

Sample Size Verification of Travel Time Measurements

The minimum required sample size of travel time observations for a certain vehicle type before or after truck prohibition (for a specific 30-minute time period) can be computed by the following formula.

(9) $$n \geq \frac{t^2_{1-\frac{d}{2},n-1} \times C^2}{D^2}$$

where,

$t_{1-\frac{d}{2},n-1}$ Student distribution with (1-d)*100% confidence level and n-1 degrees of freedom.

C – Sample Coefficient of Variance (ratio of the sample Standard Deviation to the mean).

n – the required number of travel time observations for a specific vehicle type during the defined time period.

D – precision interval as a proportion of the mean (%).

This formula helps "to estimate the minimum sample size needed to achieve any desired precision intervals or confidence levels" (Traffic Monitoring Guide 2013).

The TMG (2013) recommends the integration of a confidence level of 95% and precision intervals of ±10% for traffic engineering purposes in order to determine sample size requirement. The typical sample size results presented in Table 1 (Arazim-Harel Interchange, 17:00-17:30) show that the precision level does not exceed 10% except the heavy vehicle travel time observations after truck prohibition, which resulted in D= ±11.2%. A possible clarification for the slight deviation in precision level is that the heavy vehicle type of this typical time period and road segment might have been less homogeneous in terms of gross weight and vehicle performance characteristics.

Summary of Data Analysis Results: Average Travel Time, Traffic Volume, Total Travel Time

Table 3 and Table 4 present a summary of the data analysis of the parameters examined: travel time (TT), traffic volume (Vol), and total travel time (TTT), before the truck prohibition and after truck prohibition, respectively. The measurement unit of the parameter total travel time is: [vehicle · hours]. Its total values (measured by vehicle · hours) in Table 3 and Table 4 indicate the total travel time in the system (segments 1-8) during the analysis period. The average travel time appears in minutes-seconds format. The total travel time appears in hours-minutes-seconds format (partial seconds are taken into account in the before-after analysis).

Figure 3 present graphically the "before and after" truck prohibition results of the traffic speed parameter (S). The results presented in Tables 3 and 4 and in Figures 3 encompass the before-after two-sample t-test results (i.e., analyzed results) of the average travel time, total travel time, and average speed parameters.

From Tables 3 and 4, we can observe that the weighted average travel time of all vehicles is almost identical to the average travel time of the light vehicles, since their volume governs the traffic stream.

Heavy and Medium Vehicle Traffic Volume Evaluation:

It appears that the implementation of truck prohibition significantly affected the medium vehicle type (single unit trucks) but affected only slightly the heavy vehicle type (percentage reduction

Table 1: "Before-After" Travel Times for Arazim-Harel Segment: 17:00-17:30

Arazim-Harel 17:00-17:30	**Travel Time (minutes), before truck prohibition**			**Travel Time (minutes), after truck prohibition**		
Vehicle type	**Light**	**Medium**	**Heavy**	**Light**	**Medium**	**Heavy**
Number of observations (n)	10	8	17	12	9	12
Mean (m)	6.13	6.54	6.97	3.99	4.18	4.52
Standard deviation (s)	0.597	0.381	0.399	0.6275	0.353	0.794
Coefficient of variance (s/m)	9.74%	5.83%	5.72%	15.72%	8.45%	17.55%
$W_i = s^2/n$	0.0356	0.0182	0.0094	0.03281	0.01384	0.05254
Estimated degree of freedom (d.f.)				19.61	14.41	14.95
t (d.f., 0.05/2)				2.093	2.14479	2.14479
t (actual)				8.18	13.22	9.85
p-value				1.203E-07	2.667E-09	1.1322E-07
Significance				*significant*	*significant*	*significant*
Sample size verification						
Confidence level	95%	95%	95%	95%	95%	95%
t (df, 0.05/2)	2.26	2.36	2.11	2.20	2.306	2.201
Critical precision level, D(%)	±7.0%	±5.0%	±3.0%	±10.0%	±6.5%	±11.2%
Computed sample size	9.90	7.59	16.36	11.98	8.98	11.90

difference of 33.4% vs. 1.1%, correspondingly, Table 5). A possible reason is that most heavy vehicles during the afternoon peak hours (16:00-18:00) were non prohibited vehicles, i.e., mostly public transport buses which are more frequent during the afternoon rush hours, and partially permitted vital trucks weighting more than 12 tons.

Table 5 summarizes the traffic volume of medium plus heavy vehicles, which basically consist of all slower vehicles in the traffic stream including buses, which are faster than trucks. Table 5 indicates that the truck prohibition reduced 15.4% of the weighted average traffic volume of

Table 2: Summary of Results of the "Before-After" Analysis of the Arazim-Harel Segment: 16:00-18:00

	d.f.	t (actual)	p-value (2 tailed)	Average Travel Time (min.): Before (observed)	Average Travel Time (min.): After (observed)	Significance	Average Travel Time (min.): Before (analyzed)	Average Travel Time (min.): After (analyzed)
Light vehicle								
16:00-16:30	18.96921	7.4353	6.84E-07	00:07:08	00:05:31	significant	00:07:08	00:05:31
16:30-17:00	15.21708	9.6167	8.336E-08	00:07:02	00:05:12	significant	00:07:02	00:05:12
17:00-17:30	19.60568	8.1796	1.203E-07	00:06:08	00:03:59	significant	00:06:08	00:03:59
17:30-18:00	8.294433	10.832	4.66E-06	00:05:40	00:02:58	significant	00:05:40	00:02:58
Medium vehicle								
16:00-16:30	17.1888	5.1327	8.309E-05	00:07:21	00:06:09	significant	00:07:21	00:06:09
16:30-17:00	9.980035	4.0333	0.00296	00:07:24	00:05:45	significant	00:07:24	00:05:45
17:00-17:30	14.40968	13.223	2.666E-09	00:06:33	00:04:11	significant	00:06:33	00:04:11
17:30-18:00	22.90058	6.42	1.8493E-06	00:05:43	00:03:33	significant	00:05:43	00:03:33
Heavy vehicle								
16:00-16:30	23.04125	4.7235	9.272E-05	00:08:31	00:06:11	significant	00:08:31	00:06:11
16:30-17:00	16.78354	11.046	6.763E-09	00:07:54	00:05:35	significant	00:07:54	00:05:35
17:00-17:30	14.94766	9.8457	1.132E-07	00:06:58	00:04:26	significant	00:06:58	00:04:26
17:30-18:00	16.85941	5.1498	9.686E-05	00:05:44	00:03:31	significant	00:05:44	00:03:31

medium plus heavy vehicles. This percentage is significant taking into account that buses, which are not prohibited (and are generally estimated in Highway 1 as approximately half of total heavy plus medium vehicles), are included in this calculation. The percentage of these two vehicle types in the traffic stream (from the total volume of light + medium + heavy vehicle) was reduced from 7.0% to 6.0% after truck prohibition.

The weighted average of traffic volumes of all eight segments was based on segment length in order to obtain these equivalent percentages.

Table 3: Data Analysis of Traffic Volume, Travel Time, and Total Travel Time Before the Prohibition (16:00-18:00)

Hgwy 1 West: (before)	**Average travel time (min.) 16:00-18:00**			**Total 16:00-18:00**
Before Restriction (full data)	Light vehicles	Medium vehicles	Heavy vehicles	
Sakharov Gardens - Arazim (1)	0:02:11	0:02:08	0:02:05	0:02:11
Arazim - Harel (2)	0:06:29	0:06:49	0:07:14	0:06:31
Harel - Hemed (3)	0:01:27	0:01:39	0:01:46	0:01:28
Hemed - Shoresh (4)	0:03:57	0:04:15	0:04:09	0:03:58
Shoresh - Shaar Hagai (5)	0:05:14	0:05:53	0:06:14	0:05:17
Shaar Hagai - Latrun (6)	0:02:34	0:02:51	0:02:54	0:02:36
Latrun - Anava (7)	0:04:39	0:05:22	0:05:19	0:04:42
Anava - Daniel (8)	0:02:30	0:02:52	0:02:52	0:02:32
	Number of vehicles 16:00-18:00			**Total 16:00-18:00**
Sakharov Gardens - Arazim (1)	3863	116	210	4189
Arazim - Harel (2)	6298	210	269	6777
Harel - Hemed (3)	5100	192	146	5438
Hemed - Shoresh (4)	5289	211	243	5743
Shoresh - Shaar Hagai (5)	5316	154	211	5681
Shaar Hagai - Latrun (6)	4323	145	183	4651
Latrun - Anava (7)	4208	126	175	4509
Anava - Daniel (8)	3799	141	156	4096
Weighted Average	**4683**	**156**	**195**	**5034**
	Total travel time (vehicle·hours) 16:00-18:00			**Total 16:00-18:00**
Sakharov Gardens - Arazim (1)	140:45:49	4:08:20	7:17:12	152:11:22
Arazim - Harel (2)	680:36:44	23:52:03	32:26:02	736:54:49
Harel - Hemed (3)	122:46:28	5:15:35	4:17:14	132:19:17
Hemed - Shoresh (4)	348:30:21	14:56:25	16:50:14	380:17:01
Shoresh - Shaar Hagai (5)	463:25:37	15:06:29	21:53:33	500:25:38
Shaar Hagai - Latrun (6)	185:27:45	6:53:11	8:51:54	201:12:50
Latrun - Anava (7)	326:32:03	11:15:41	15:30:10	353:17:54
Anava - Daniel (8)	158:47:37	6:44:59	7:26:21	172:58:57
Total (vehicle·hours)	**2426:52:24**	**88:12:43**	**114:32:41**	**2629:37:49**

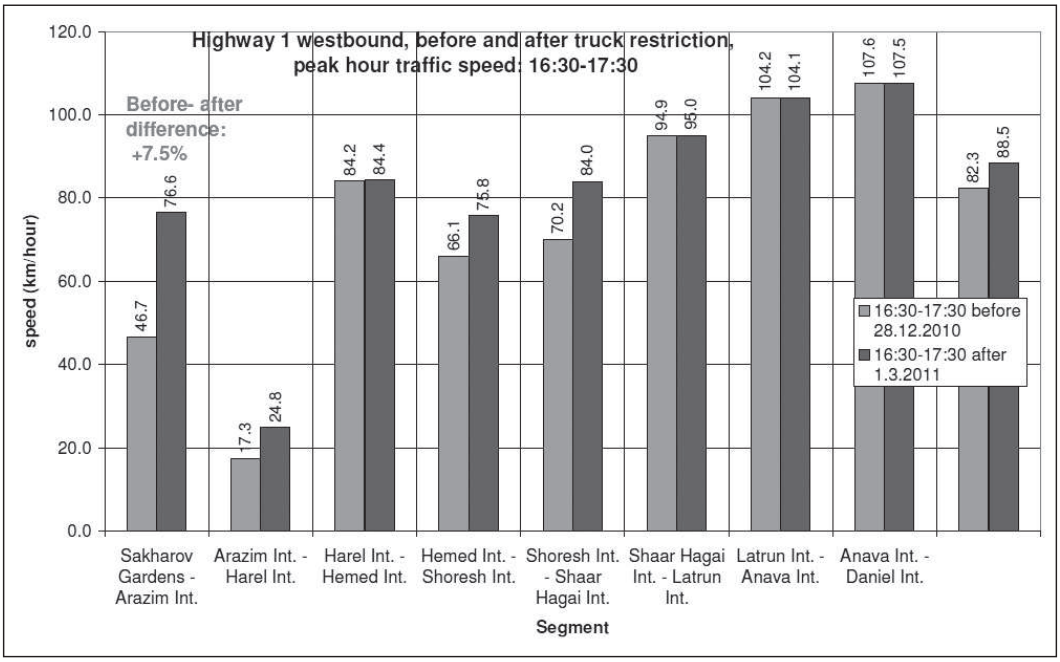
Table 4: Data Analysis of Traffic Volume, Travel Time, and Total Travel Time After the Prohibition (16:00-18:00)

Hghwy 1 West: (after)	**Average travel time (min.) 16:00-18:00**			**Total 16:00-18:00**
After Restriction (full data)	Light vehicles	Medium vehicles	Heavy vehicles	
Sakharov Gardens - Arazim (1)	0:01:29	0:01:40	0:01:41	0:01:30
Arazim - Harel (2)	0:04:28	0:05:04	0:05:03	0:04:28
Harel - Hemed (3)	0:01:27	0:01:39	0:01:47	0:01:27
Hemed - Shoresh (4)	0:03:32	0:03:48	0:03:49	0:03:33
Shoresh - Shaar Hagai (5)	0:05:12	0:05:14	0:05:52	0:05:13
Shaar Hagai - Latrun (6)	0:02:38	0:02:51	0:02:51	0:02:39
Latrun - Anava (7)	0:04:38	0:05:14	0:05:14	0:04:41
Anava - Daniel (8)	0:02:31	0:02:52	0:02:52	0:02:32
	Number of vehicles 16:00-18:00			**Total 16:00-18:00**
Sakharov Gardens - Arazim (1)	4127	67	197	4391
Arazim - Harel (2)	6596	141	235	6972
Harel - Hemed (3)	5151	118	126	5395
Hemed - Shoresh (4)	5283	123	235	5641
Shoresh - Shaar Hagai (5)	5374	116	201	5691
Shaar Hagai - Latrun (6)	4557	95	185	4837
Latrun - Anava (7)	4194	107	192	4493
Anava - Daniel (8)	3281	62	160	3503
Weighted Average (vehicles)	**4683**	**104**	**193**	**4980**
	Total travel time (vehicle·hours) 16:00-18:00			**Total 16:00-18:00**
Sakharov Gardens - Arazim (1)	101:56:24	3:06:12	5:30:14	110:32:49
Arazim - Harel (2)	490:09:50	17:59:42	19:44:55	527:54:28
Harel - Hemed (3)	123:47:20	4:40:58	3:44:47	132:13:06
Hemed - Shoresh (4)	310:41:26	11:00:40	14:54:58	336:37:03
Shoresh - Shaar Hagai (5)	465:16:41	13:52:50	19:37:55	498:47:26
Shaar Hagai - Latrun (6)	199:58:01	6:44:44	8:46:57	215:29:42
Latrun - Anava (7)	324:25:56	13:00:49	16:44:13	354:10:57
Anava - Daniel (8)	137:13:50	4:24:17	7:38:43	149:16:49
Total (vehicle·hours)	**2153:29:28**	**74:50:11**	**96:42:41**	**2325:02:19**

Table 5: Impact Summary of Truck Restriction on Combined Traffic Volume of Medium Plus Heavy Vehicles (16:00-18:00)

Segment	Before		After				
	Medium + heavy vehicle volume	Medium vehicle volume	Medium + heavy vehicle volume	Medium vehicle volume	Percentage difference (before-after): medium + heavy vehicle	Percentage difference (before-after): medium vehicle	Percentage difference (before-after): heavy vehicle
Sakharov Gardens - Arazim (1)	326	116	264	67	-19.02%	-42.24%	- 6.19%
Arazim - Harel (2)	479	210	376	141	-21.50%	-32.86%	- 12.64%
Harel - Hemed (3)	338	192	244	118	-27.81%	-38.54%	- 13.70%
Hemed - Shoresh (4)	454	211	358	123	-21.15%	-41.71%	- 3.29%
Shoresh - Shaar Hagai (5)	365	154	317	116	-13.15%	-24.68%	- 4.74%
Shaar Hagai - Latrun (6)	328	145	280	95	-14.63%	-34.48%	1.09%
Latrun - Anava (7)	301	126	299	107	-0.66%	-15.08%	9.71%
Anava - Daniel (8)	297	141	222	62	-25.25%	-56.03%	2.56%
Weighted average volume (based on segment length)	**351**	**156**	**297**	**104**	**-15.4%**	**-33.4%**	**-1.06%**

Figure 3: Before and After Traffic Speeds (S)



EXAMINATION OF THE PILOT STUDY PARAMETERS

The following parameters were examined before and after the truck prohibition: average travel time (ATT), total travel time (TTT) for the whole prohibition period (16:00-18:00), and average travel speed (S) for the peak hour (16:30-17:30) of the prohibition period. The percentage difference between before and after application of the truck prohibition was computed for each parameter. The computations were performed for the individual segment and for the total highway section. Equations (9) and (10) show the computations only for the ATT parameter. The computations for the two other parameters (TTT, S) examined to test the success of the pilot study were conducted in a similar format.

Percentage Difference for the Individual Segment:

$$(10)\quad \%ATT_k = \frac{(ATT_k(A)) - (ATT_k(B))}{(ATT_k(B))}$$

ATT_k (A) – average travel time for segment k after the truck prohibition
ATT_k (B) – average travel time for segment k before the truck prohibition
$\%ATT_k$– Travel time percentage difference before and after the truck prohibition for segment k.

Percentage Difference for the Whole Section:

$$(11)\quad \%ATT = \frac{(ATT(A)) - (ATT(B))}{(ATT(B))}$$

ATT (A) – average travel time for the whole highway section after the truck prohibition.
ATT (B) – average travel time for the whole highway section before the truck prohibition.

%ATT– Travel time percentage difference before and after the truck prohibition for the whole highway section.

Tables 6.1-6.3 present a summary of the analyzed results and the percentage difference of the three traffic parameters analyzed: ATT, TTT, and respective average speeds after implementation of the t-test results. The format of ATT and TTT in Tables 6.1, 6.2 is the same as in Table 3 and Table 4, i.e., minutes-seconds and hours-minutes-seconds, correspondingly. A decimal format of minutes and hours was supplemented in parentheses.

The analyzed results are based on equalizing of the non-significant sample outcomes for the purpose of examining the pilot study.

The results show that the pilot study was successful in regard to the three analyzed parameters: the ATT per vehicle decreased by 11.0%; the TTT decreased by 11.6%; and the average speed increased by 7.5%. The prohibition of trucks during the afternoon peak hours assisted in relieving congestion even though the total traffic volume slightly increased (Figure 2).

Table 6.1: Average Travel Time Results (Analyzed), Before and After Truck Prohibition

Road segment (16:00-18:00)	**Distance (km)**	**Avg. TT per vehicle (min.): Before [analyzed]**	**Avg. TT per vehicle (min.): After [analyzed]**	**% difference Avg. TT per vehicle: [analyzed]**
Sakharov Gardens - Arazim (1)	1.914	0:02:11 (2.180)	0:01:30 (1.494)	-31.5%
Arazim - Harel (2)	1.912	0:06:31 (6.524)	0:04:28 (4.469)	-31.5%
Harel - Hemed (3)	2.064	0:01:28 (1.460)	0:01:27 (1.454)	-0.4%
Hemed - Shoresh (4)	4.676	0:03:58 (3.973)	0:03:33 (3.546)	-10.7%
Shoresh - Shaar Hagai (5)	6.588	0:05:17 (5.285)	0:05:13 (5.219)	-1.3%
Shaar Hagai - Latrun (6)	4.076	0:02:36 (2.596)	0:02:39 (2.645)	1.9%
Latrun - Anava (7)	8.098	0:04:42 (4.701)	0:04:41 (4.681)	-0.4%
Anava - Daniel (8)	4.600	0:02:32 (2.534)	0:02:32 (2.532)	-0.1%
Total (minutes)	33.928	**0:29:15 (29.253)**	**0:26:02 (26.041)**	**-11.0%**

Table 6.2: Total Travel Time (TTT) Results (Analyzed), Before and After Truck Prohibition

Road segment (16:00-18:00)	**Distance (km)**	**TTT (vehicle·hours): Before [analyzed]**	**TTT (vehicle·hours): After [analyzed]**	**% difference Avg. TTT: [analyzed]**
Sakharov Gardens - Arazim (1)	1.914	152:11:22 (152.189)	110:32:49 (110.547)	-27.4%
Arazim - Harel (2)	1.912	736:54:49 (736.914)	527:54:28 (527.908)	-28.4%
Harel - Hemed (3)	2.064	132:19:17 (132.321)	132:13:06 (132.218)	-0.1%
Hemed - Shoresh (4)	4.676	380:17:01 (380.283)	336:37:03 (336.618)	-11.5%
Shoresh - Shaar Hagai (5)	6.588	500:25:38 (500.427)	498:47:26 (498.790)	-0.3%
Shaar Hagai - Latrun (6)	4.076	201:12:50 (201.214)	215:29:42 (215.495)	7.1%
Latrun - Anava (7)	8.098	353:17:54 (353.298)	354:10:57 (354.182)	0.3%
Anava - Daniel (8)	4.600	172:58:57 (172.983)	149:16:49 (149.280)	-13.7%
Total (vehicle·hours)	33.928	**2629:37:49 (2629.630)**	**2325:02:19 (2325.039)**	**-11.6%**

Table 6.3: Peak-Hour Travel Speed (S) Results (Analyzed), Before and After Truck Prohibition

Road segment (16:30-17:30)	Distance (km)	Avg. S (km/hr): Before [analyzed]	Avg. S (km/hr): After [analyzed]	% difference Avg. Speed: [analyzed]
Sakharov Gardens - Arazim (1)	1.914	46.7	76.6	64.1%
Arazim - Harel (2)	1.912	17.3	24.8	43.6%
Harel - Hemed (3)	2.064	84.2	84.4	0.2%
Hemed - Shoresh (4)	4.676	66.1	75.8	14.7%
Shoresh - Shaar Hagai (5)	6.588	70.2	84.0	19.7%
Shaar Hagai - Latrun (6)	4.076	94.9	95.0	0.1%
Latrun - Anava (7)	8.098	104.2	104.1	0.0%
Anava - Daniel (8)	4.600	107.6	107.5	0.0%
Entire section	33.928	**82.3**	**88.5**	**7.5%**

The improvement in average travel time (ATT) and speed (S) resulting from the truck prohibition was significant along segments 1, 2, and 4. The TTT parameter showed a significant improvement in segments 1, 2, 4, and 8. The speed (S) parameter showed a significant improvement in segment 5, too (during the peak hour 16:30-17:30). This improvement is balanced during the entire truck restriction period (16:00-18:00) due to an exceptional advantage in the ATT during the first half-hour period (16:00-16:30) before the truck prohibition. These improvements imply that the presence of trucks in the traffic stream disrupt the regular highway traffic. Essentially, drivers need to make difficult maneuvers of passing and lane changing, which could entail rear-end or side-end collisions.

The pilot study results showing improvements in the three parameters offer a good reason for implementing the truck prohibition only along segments 1-4. However, since there is no feasible alternative route to these segments for trucks, the Ministry of Transportation (MOT) implemented the truck prohibition along the entire section (segments 1-8) as originally planned.

QUALITATIVE EVALUATION AND DISCUSSION OF ROAD-SEGMENT GRADE EFFECT AND HCM PROCEDURE

The grade effect was evaluated to examine whether the grade level of each road segment was correlated with an improvement in traffic flow parameters. Table 7 presents the longitudinal grade level of the eight road segments. A summary is also provided of the percentage difference of the three traffic flow parameters, based on the analyzed results of Tables 6.1-6.3. The percentages in Table 7 are given as improvement percentages in order to unify the results to one average improvement outcome for each road segment.

Table 7 shows that improved average percentage results are correlated with longitudinal grade level. The level terrain corresponds to 0-2%; the moderate grade level corresponds to 2.1-4%; and the steep terrain corresponds to 4.1-6%.

Road segments 1, 2, and 4, which have the most significant improvements, have full or partial steep grades (either a steep descent or a steep rise). Segments 1 and 2, each of which presents a full, steep longitudinal grade, have the best percentage improvements (41% and 35%, respectively). Road segment 4, which has a partially steep and partially level terrain, resulted in a lower percentage improvement (12.3%) after the truck restriction. Segment 3 is the only segment for which there was no percentage improvement even though it has a steep grade along 55% of its alignment. This can be explained by the fact that the segment has much less horizontal curvature than do segments 1, 2, and 4, and is the only segment that has an additional lane per direction. The travel speed along Segment 3 was comparatively high even before the truck prohibition (approximately 85 km/hour) apparently because of its relatively straight descent and supplementary lane.

Road segments 5 and 8, which have no steep grade (a partial alignment of level terrain and a partial alignment of a moderate longitudinal grade), have a lower percentage improvement in the traffic flow parameters from the truck restriction. Road segments 6 and 7, whose terrain is partially level and partially moderate (similar to segments 5 and 8), have no percentage improvement in the traffic parameters examined. It appears that since the rise in the alignment of segments 5 and 8 is more than that of segments 6 and 7, the impact of the truck restriction on the former two segments is larger. The moderate rise causes more reductions in truck speed than does a moderate descent (or a level terrain) and, therefore, a better improvement in the traffic flow parameters with the truck prohibition.

Generally, the effect of a steep grade is correlated with the exclusion of heavy trucks from the traffic stream in terms of saving travel time and increasing the speed of the traffic stream. This outcome is relatively consistent with Cate and Urbanik's (2004) study, which concluded that a left-lane restriction—not a directional truck restriction as examined in this study—improved travel time with an increased grade but at lower percentages than found in the current study.

Highway Capacity Manual (HCM) Relevance Discussion

The Highway Capacity Manual (2000, 2010) provides a procedure for estimating the impact of different trucks' percentage with consideration of highway grades. Theoretically, the implementation of time of day restriction strategy, utilized in the current study (by prohibiting trucks from all lanes per direction), could be based on the HCM procedure after measuring the traffic volumes only (before and after truck restriction) by vehicle type.

HCM Procedure Overview for Implementation in the Current Study. The HCM procedure (for basic freeway segments or multi-lane highway segments) uses the heavy vehicle adjustment factor (f_{HV}) to calculate the equivalent passenger car flow rate (Vp) and finally evaluates the section Level of Service (LOS).

The equivalent passenger car flow rate (Vp) can be determined by the equation:

$$(12)\quad V_P = \frac{V}{(PHF \cdot f_{HV})}$$

V: hourly volume (vehicle/ hour)
PHF: peak hour factor.

On the basis of the flow rate, Vp, and the speed-flow curves proposed by HCM (2000, 2010) and estimation of the actual Free Flow Speed (FFS), the average speed and the resulted average travel time of a specific segment can be determined.

HCM Procedure Limitations for the Purpose of the Current Study. The HCM procedure has some limitations for obtaining the average speed and the resulted average travel time, which are essential parameters to evaluate the success of implementing the truck prohibition in the current study.

The advantage of the procedure proposed in the current study is the determination of average travel time and average speed parameters of a specific segment by direct measurements without the need of several steps to obtain these parameters.

The HCM procedure does not provide the travel time and speed parameters directly. The composite grade along a specific segment and the multi-stage HCM methodology (e.g., Exhibit 23.1 in HCM 2000 for basic freeway segments) including the FFS approximation requirement, make the use of HCM procedure prolonged and probably prone to inaccuracies, especially for the current pilot segments' analysis. Also, the HCM flow-speed curves of basic freeway or multi-lane segments are

Table 7: Qualitative Level of Longitudinal Grade Effect and Percentage Improvement in ATT, TTT, and Speed

Road segment	Distance (km)	Longitudinal grade level	% improvement Avg. TT per vehicle: [analyzed] 16:00-18:00	% improvement Avg. TTT per vehicle: [analyzed] 16:00-18:00	% improvement Avg. Speed: [analyzed] 16:30-17:30	Avg. % improvement
Sakharov Gardens - Arazim (1)	1.914	**SD**	31.5%	27.4%	64.1%	41.0%
Arazim - Harel (2)	1.912	**SR**	31.5%	28.4%	43.6%	34.5%
Harel - Hemed (3)	2.064	55% **SD**, 45% MD	0.4%	0.1%	0.2%	0.23%
Hemed - Shoresh (4)	4.676	50% **SR**, 50% LT	10.7%	11.5%	14.7%	12.3%
Shoresh - Shaar Hagai (5)	6.588	35% MD, 30% MR, 35% LT	1.3%	0.3%	19.7%	7.1%
Shaar Hagai - Latrun (6)	4.076	40% LT, 60% MD	-1.9%	-7.1%	0.1%	-2.97%
Latrun - Anava (7)	8.098	45% LT 45% MD 10% MR	0.4%	-0.3%	0.0%	0.03%
Anava - Daniel (8)	4.600	35% LT, 45% MD, 25% MR	0.1%	13.7%	0.0%	4.6%

SD=Steep Descent, SR=Steep Rise, LT=Level Terrain, MD=Moderate Descent, MR=Moderate Rise

limited to average speeds that are not lower than 50 km/hr, whereas speeds lower than 50 km/hour, which are considered LOS F in the HCM procedure, were observed in the current study.

Nonetheless, the HCM procedure which requires traffic volume data and trucks' composition only, is essential and fundamental for obtaining the traffic flow LOS. If we consider the average travel speed and calculate the flow rate based on traffic volume and travel time measurements per segment, we can derive the flow density (in passenger cars per hour per lane) and eventually evaluate the LOS of each segment (hourly based) without referring to the speed-flow curves of HCM.

POLICY CONSIDERATIONS

Israel MOT policy regarding truck restriction also includes directing heavy truck traffic (which is restricted in Highway 1) to an alternate route. This route is multi-lane highway 443, which can transfer truck traffic from the Jerusalem exit to the Modi'in area (Ben Shemen Interchange) and merge to Highway 1-westbound (Figure 4). Different policies such as a High Occupancy Toll (HOT) lane or a lower speed lane have been found not practical in terms of traffic load Right of Way (ROW) constraints. In most Highway 1 segments, there are two lanes per direction and the right shoulder is not continuously wide enough to be used as a peak period traveling lane for heavy trucks, without depreciating traffic flow if one of the two regular lanes (e.g., a lower speed limit lane) is prohibited for regular traffic.

The threshold of a 12-ton truck weight is a compromised strategy of Israel MOT in order to minimize the economic disadvantage to trucking companies and industry manufacturers. One rear-axle trucks, which weigh less than 12 tons, are characterized by better speed–distance curves' performance for tangent grades and also a better performance during their acceleration while making a merging maneuver from an interchange entrance ramp terminal. The larger dimensions of heavy trucks cause a significant disturbance to the traffic stream, increase the conflicts between vehicles, and therefore have a higher potential for traffic accidents. Nonetheless, this strategy reduced significantly the volume of medium vehicles in the traffic stream (compared with heavy vehicle type), including one rear-axle single unit (SU) trucks that could weigh more than 12 tons (Table 5). A typical commercial vehicle, which is implemented for designing climbing lanes in Israel and in other countries (Canada, TAC ATC 1999; PIARC 2003, Barton 2009, Ireland TD 2007 etc.), has a mass/power ratio of 8 HP/ton (170 kg/kwatt, 5.9 Kwatt/ton). This property usually matches the 12-ton trucks. According to Israel MOT traffic regulations and other sources (Hardwood et al. 2003), the threshold weight of two-axle vehicle SU trucks is 18 tons. This can clarify the outcome of significant decrease of medium vehicle types after truck prohibition.

Truck performance considerations and trucking companies' feedback directed Israel MOT to permit lighter trucks (weighing less than 12 tons) to continue using Highway 1. The option of determining different weight thresholds in different segments along the route examined may confuse truck drivers and is not feasible in terms of finding an alternate route and weight enforcement.

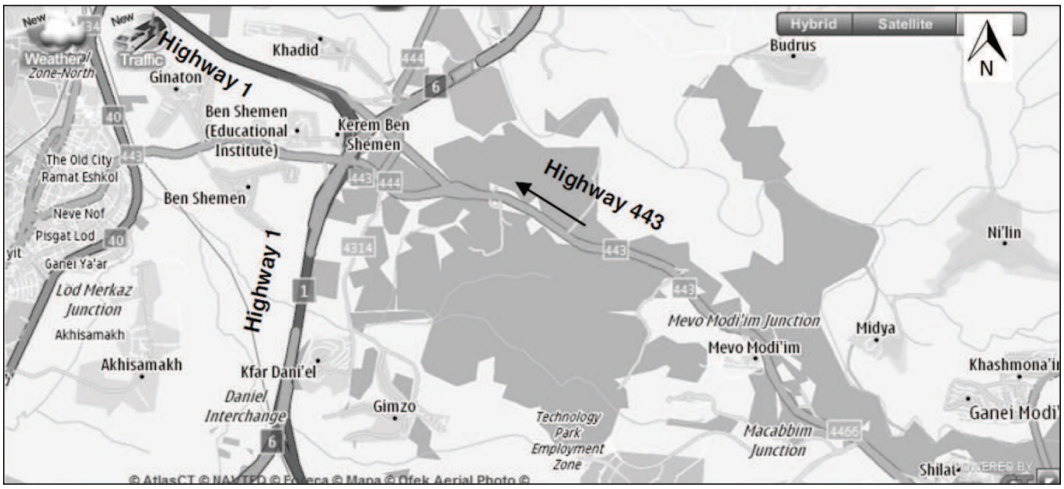
Road Pricing Potential

The amount of traffic in the analyzed section does not justify peak period road pricing strategy. Since the truck restriction strategy improved traffic flow, it was regarded as a reasonable policy solution, especially with integrating an alternate route.

In Israel, the access to the Tel Aviv metropolitan area by Highway 1 is more congested. Israel MOT considered overall road pricing as a possible solution but finally implemented a supplemental HOT lane toward Tel Aviv (westbound direction) from Ben Gurion International Airport. This solution was accompanied by constructing a large park & ride lot and allocating shuttle service to the passenger car drivers. This solution provides passenger car drivers the option to decide whether to follow the toll pricing policy, use the HOT lane and pay for the privilege, or park their car and use the shuttle bus service without paying, or continue using the regular congested lanes without saving travel time.

The topography of Ben Gurion Airport–Tel Aviv section is level terrain, so the problem of slow trucks is not prominent as in the Highway 1 studied section during the entrance to or the exit from the Jerusalem metropolitan area. It appears that the exclusion of trucks along the access to Tel Aviv would increase the regular traffic load of passenger cars anyway.

Figure 4: Merging from Highway 443 to Highway 1 (Ben-Shemen Interchange)



SUMMARY AND CONCLUSION

This study investigated the traffic operation efficiency gained by restricting heavy- truck traffic along 34 kilometers of Israel's Highway 1 in a westbound direction, exiting the city of Jerusalem during afternoon peak hours. The terrain of the section examined is partially hilly and includes several horizontal and vertical curves. The examination was performed during the rush hours although truck traffic volume does not necessarily tend to peak during the regular morning and afternoon commuter peaks. The possibility that trucks may cause a deterioration in both traffic flow quality and traffic capacity, the formation of long queues and merging, diverging, and weaving difficulties occurs during the peak hour period and not during the peak of truck traffic when the traffic stream is light.

The major objective of the study was to estimate the benefit of restricting truck traffic according to three traffic flow parameters: (1) average travel time (ATT), (2) total travel time (TTT), and (3) average traffic speed (S). The analyzed results, which considered the significant differences among samples during 30-minute periods based on two sample t-tests ("before-after" the truck restriction), show an 8%-12% improvement in all three traffic flow parameters by applying the truck prohibition to all lanes during the peak afternoon period of 16:00-18:00. Specifically, of the highway section examined, segments 1 and 2, each of whose full alignment consists of a steep longitudinal grade, experienced the most significant improvements in the parameters examined (41% and 35%, respectively). Road segment 4, which has a partial alignment of steep longitudinal grade and a partial alignment of level terrain, showed a lower percentage improvement (only 12%) than did road segments 1 and 2.

The combined results of the entire section examined (Sakharov Gardens-Daniel Interchange) reveal a consistent outcome of improved traffic flow insofar as all three parameters examined. This finding contrasts with some previous studies that evaluated the impact of lane-use restriction for trucks and that partially produced non-conclusive outcomes and even potential vehicle conflicts (e.g., merging and diverging conflicts along the right lane).

The methodology proposed by this study is preferable than the HCM Level of Service (LOS) multi-stage analysis procedure, which is subject to inaccuracies and is limited to higher portions of average travel speed.

We recommend to examine the results by additional data sets, and increased samples of travel time samples and by similar restrictions on additional rural freeways or multi-lane highway road segments because of the differences that could result from alternate geometrics, operational characteristics, and traffic pattern.

Furthermore, the methodology presented in this present study can be implemented on other roadways, rural or urban, with different geometric and traffic characteristics, especially highways carrying a significant amount of heavy vehicles that disrupt the traffic flow and risk the safety of passenger car drivers. Applying the present methodology on roadways having different operational and geometric characteristics from those in this study, such as urban freeways, might generate a different outcome. Prohibition of trucks in urban freeways during rush hours might bring additional daily passenger cars traffic to the traffic stream, which could negatively result in an insignificant improvement of traffic operation and even a slight deterioration of the traffic flow quality.

References

Barton D. *Guide to Road Design Part 3: Geometric Design.* AUSTROADS. Sydney, Australia, 2009.

Cate, M.A. and T. Urbanik, (2004). "Another View of Truck Lane Restrictions." *Transportation Research Record* 1967, (2004): 19-24.

El-Tantawy S., S. Djavadian, M. J. Roorda, and B. Abdulhai. "Safety Evaluation of Truck Lane Restriction Strategies Using Microsimulation Modeling." *Transportation Research Record* 2099, (2009): 123-131.

Ferrari P. "The Effect of the Competition Between Cars and Trucks on the Evolution of the Motorway Transport System." *Transportation Research C.* 17, (2009): 558-570.

Ferrari P. "The Dynamics of the Competition Between Cars and Trucks on Motorways." *Transportation Research C.* 19, (2011): 579-592.

Grenzeback L.R., W.R. Reilly, P.O. Roberts, and J.R. Stowers. "Urban Freeway Greedlock Study: Decreasing the Effects of Large Trucks on Peak Period Urban Freeway Congestion." *Transportation Research Record* 1256, (1990): 16-26.

Harwood D.W., D.J. Torbic, K.R. Richard, W.D. Glauz, and L. Elefteriadou. *Review of Truck Characteristics as Factors in Roadway Design.* National Cooperative Highway Research Program. *NCHRP Report 505.* 2003.

Highway Capacity Manual. *Special Report 209*, Transportation Research Board, Third Edition, 2000.

Highway Capacity Manual. Transportation Research Board. Fourth Edition. 2010.

Hoel, L.A. and J.L. Peek. *Simulation Analysis of Traffic Flow Elements for Restricted Truck Lanes on Interstate Highways in Virginia.* Final Report for Virginia Department of Transportation, Virginia Transportation Research Council, Charlottesville, Virginia, 1999.

Jo, S., A. Gan, and G. Bonyoni. "Impact of Truck Lane Restrictions on Freeway Traffic Operations." 82nd TRB annual meeting, Washington D.C., 2003.

Lord D., D. Middleton, and J. Whitacre. "Does Separating Trucks from Other Traffic Improve Overall Safety?" *Transportation Research Record* 1922. (2005): 156-166.

McCarthy, K. "Truck Speed Limits and Lane Restrictions." *OLR Research Report. R-0814*., 2005. http://cga.ct.gov/2005/rpt/2005-R-0814.htm.

Moses, R., G. Price, and S. Siuhi. "Evaluating the Effectiveness of Various Truck Lane Restrictions Practices in Florida, Phase II. Volume I: Simulation Analysis of I-95 Corridor with Truck Lane Restriction." Florida Department of Transportation, Tallahassee, Florida, 2007.

Mussa, R. "Safety and Operational Evaluation of Truck Lane Restriction." *Journal of Transportation Research Forum*, 43(2), (2004): 117-127.

NRA – National Roads Authority. *Road Link Design.* 6(1), Part 1 – NRA TD 9/07, Dublin, Ireland, 2007.

PIARC. *Road Safety Manual.* Recommendations from the World Road Association. PIARC Technical Committee on Road Safety (C13), 2003.

Qi Y., S. Ishak, B. Wolshon, C. Alecsandru, and X. Sun. "Effect of Truck Lane Restriction and Differential Speed Limit on Traffic Characteristics of Four-Lane Rural Freeways." TRB 88th Annual Meeting Compendium of Papers DVD. 09-1246, 2009.

Satterthwaite, F. E. "An Approximate Distribution of Estimates of Variance Components." *Biometrics Bulletin 2*, (1946): 110–114.

Siuhi S. and R. Mussa. "Simulation Analysis of Truck-Restricted and High-Occupancy Vehicle Lanes." *Transportation Research Record.* 2012, (2007): 127-133.

Stokes, R.W. and W.R. McCasland. "Truck Operations and Regulations on Urban Freeways in Texas." *ITE Journal* 56 (1986): 17-21.

TAC- Transportation Association of Canada. *Geometric Design Guide for Canadian Roads.* Ottawa, Canada, 1999.

Traffic Monitoring Guide. *Federal Highway Administration Monitoring Guide.* US Department of Transportation. Federal Highway Administration. Office of Highway Policy Information, 2013.

Welch, B. L. "The Generalization of "Student's" Problem when Several Different Population Variances are Involved." *Biometrika* 34*,* (1947): 28–35.

Yang C.H. and A.C. Regan. "A Multi Criteria Decision Support Methodology for Implementing Truck Operations Strategies." *Transportation* 40, (2013): 713-728.

APPENDIX A

Background: Vertical and Horizontal Curves in Highway Geometric Design

Proper design of roadway geometric design (design of road layout and road profile) is important to facilitate smooth flow of traffic and maintain traffic safety.

The basic principles of highway geometric design are generally exemplified for two highway alignment types: (1) roads with zero grade change direction (horizontal alignment), and (2) straight lines of the highway profile have different grades (vertical alignment). Although is it conceivable that two straight lines of the highway alignment that need to be joined, have different directions as well as different grades, the highway design have specific principles for horizontal alignment and vertical alignment.

Direction changes in road layout (horizontal alignment) are attained by providing curves between two straight lines in two different directions. These curves (generally circular curves) are termed horizontal curves.

Grade changes in roads are attained by providing curves between two straight lines at different grades along the highway profile (vertical alignment). These curves (generally parabolic curves) are termed vertical curves.

Shy Bassan *is a traffic and transportation engineer working in Amy-Metom Engineers & Consultants (Israel). His major fields of interests are traffic engineering and geometric design of highways. He received his B.Sc. and M.Sc. degrees in civil engineering from the Technion Israel Institute of Technology and his Ph.D. in transportation engineering from the University of Delaware (Newark). His current work focuses on revising the national guidelines of geometric design of rural and suburban highways, signalized intersection design guidelines, traffic engineering projects, traffic impact studies, and highway safety audits.*

Safety and Economic Assessment of Converting Two-Way Stop-Controlled Intersections to Roundabouts on High Speed Rural Highways

by Shanshan Zhao, Aemal J. Khattak and Eric C. Thompson

This research addressed two questions: "Are roundabouts on rural high-speed roadways safer than two-way stop controlled (TWSC) intersections?" and "What economic benefits can be expected from converting TWSC intersections to roundabouts in terms of safety improvement?" Crash and traffic data on four TWSC intersections that were converted to roundabouts in Kansas were analyzed using the empirical Bayes before-after evaluation method and crash costs were applied to evaluate economic benefits. Analysis showed that fatal, non-fatal, and property-damage-only crashes were reduced by 100%, 76.47%, and 35.49%, respectively. The annual monetary value from this reduction was between $1.0—$1.6 million in 2014 dollars.

INTRODUCTION

Construction of modern roundabouts is becoming common in the United States. Their use in the United States began in 1990s and they have been increasingly popular since then (Rodegerdts 2007). Construction of roundabouts is one way to reduce vehicle collisions and improve the efficiency of intersections (Nebraska Department of Roads 2012). Numerous studies in the United States have shown that roundabouts are effective in urban environments but published literature is relatively sparse on the safety performance of roundabouts constructed on high-speed (45-65 mph) roads in rural and suburban areas.

A concern with roundabouts constructed on high-speed rural roadways is the speed differential of vehicles traveling on the roundabout approaches and roundabout entries. Roundabouts on high-speed roadways are not "high-speed roundabouts" (Isebrands and Hallmark 2012). With a well-designed roundabout, drivers are allowed to navigate at a reduced speed (15 to 30 mph) inside the roundabout (Isebrands and Hallmark 2012, Persaud et al. 2001, Rodegerdts 2010). Inadequate signing, absence of nighttime lighting, and possible lower levels of drivers' alertness in rural environments may be some of the reasons causing high approach speeds and driver confusion at the roundabouts (Thomas and Nicholson 2003, Appleton and Clark 1998). The research questions addressed in this research therefore were: "Are roundabouts on rural high-speed roadways safer than traditional two-way stop controlled (TWSC) intersections?" and "What economic benefits can be expected for the conversion from TWSC intersections to roundabouts in terms of safety improvement?" Therefore, the objectives were to statistically quantify the changes in reported crashes before and after conversion of rural TWSC intersections with high-speed approaches to roundabouts and quantitatively evaluate the economic values of these changes.

To answer the above questions, crash records on several TWSC intersections that were subsequently converted to roundabouts were collected from Kansas Department of Transportation (KDOT). A before-after analysis using the Empirical Bayes (EB) method as given in the *Highway Safety Manual* (AASHTO 2010a) was utilized. An economic evaluation was conducted based on the results of this safety analysis. The organization of the remaining paper includes a review of pertinent literature followed by the modeling background. The next section presents results of the EB before-after crash analysis while the ensuing section shows results of the economic evaluation based on avoided crashes and reduced severities. The last section provides conclusions and a discussion.

LITERATURE REVIEW

Safety Studies on Rural Roundabouts with High-Speed Approaches

Several studies have shown that roundabouts reduce crash frequencies as well as severities compared with their traditional traffic control counterparts (Rodegerdts 2007, Persaud et al. 2001, Rodegerdts 2010, Flannery and Datta 1996, Lanani 1975, Cunningham 2007, Maycock and Hall 1984, Persaud et al. 2000, Tudge 1990). Most of the roundabouts studied were in urban settings. Studies specially pertaining to rural roundabouts with high-speed approaches were relatively sparse; however, the following studies were found on rural roundabouts with high-speed approaches in the U.S. during the literature search.

Myers (1999) studied crashes at five rural roundabouts with high-speed approaches in Maryland by analyzing data gathered three years before and three years after the installation of the roundabouts. A before-after analysis showed that the average crash rates at these five intersections were reduced by 59% and the injury or serious crashes were reduced by 80%. Persaud et al. (2001) conducted an EB observational before-after study on crashes when 23 intersections were converted from stop sign and traffic signal control to modern roundabouts. Results indicated a 40% reduction in all crashes and an 80% reduction in injury crashes. Of all the intersections, the five rural single-lane roundabouts experienced a 58% reduction in total crashes and an 82% reduction in injury crashes, which were both higher than the average of all settings. Ritchie and Lenters (2005) compared the performance of roundabouts and traffic signals with high-speed approaches (45+ mph). They reported roundabouts out-performing their signalized counterparts by nearly a 50% reduction in injury and fatal crashes; one specific site demonstrated an 80% reduction in expected crashes after conversion to roundabouts.

Rodegerdts (2007) conducted an EB before-after study comparing the performance of traditionally controlled intersections with roundabouts. The study concluded that roundabouts reduced both overall crash rates and injury crash rates in a wide range of settings including urban, suburban, and rural. All types of crashes were reduced by approximately 35.4% and injury crashes were reduced by 75.8%. For the nine rural roundabouts studied in the report, which were all converted from TWSC intersections, the total crash reduction was 71.5%, and injury crashes were reduced by 87.3%. For the 24 suburban roundabouts converted from signalized or TWSC intersections, the total crash reduction and injury crash reduction were about 42% and 68%, respectively.

In Maryland, crash reports of 149 crashes at 29 single-lane roundabouts and 134 crashes at nine double-lane roundabouts were reviewed (Mandavilli et al. 2009). Several of the roundabouts in the study were rural roundabouts on high-speed roadways; about three-quarters of all reported collisions were at the roundabout entrance, and high approach speed was an important factor in crashes.

Isebrands and Hallmark (2012) conducted a study on rural roundabouts with high-speed approaches. A before-after crash analysis using a negative binomial regression model and a before-after EB estimation were both conducted showing consistent results. The negative binomial regression showed that total crashes were reduced by 63% and injury crashes by 88% at 19 rural roundabouts with high speed approaches. The before-after EB estimation showed reductions of 67% in total crashes and 87% in injury crashes.

An evaluation of 24 roundabouts was conducted in Wisconsin (Qin et al. 2013). The EB before-after analysis showed an overall reduction of 9.2% in total crashes in all locations and a 52% reduction in fatal and injury crashes. Eight of the 24 roundabouts were identified as rural; these roundabouts experienced reductions of 45% in total crashes and 56% in fatal and injury crashes. The study included 11 roundabouts with a posted speed limit of 45 mph or greater. These roundabouts experienced reductions of 34% in total crashes and 49% in fatal and injury crashes.

A study of conversion to roundabouts in Belgium (Antoine 2005) showed an average of 42% decrease in injury crashes and 48% decrease in serious crashes in all settings. Roundabouts in rural

open country environment, which usually have high speed approaches, had a 50% crash reduction. Roundabouts in suburban locations had a crash reduction of 46% and those in urban areas a reduction of 15%.

Economic Benefits of Conversion to Roundabouts

Economic benefits can be expected from conversions of intersections to roundabouts. The main safety benefits of converting a TWSC intersection to a roundabout are the assumed savings to the public due to a reduction in crashes in the before-after periods within the project area. Non-safety related benefits may include reductions in motorist delays, fuel consumption, and vehicle emissions. Safety benefit estimation requires a crash history before and after conversion to a roundabout. The EB before-after analysis can be used to eliminate the effects of regression-to-the-mean and changes in traffic volumes during the before-after periods. Safety benefits are then estimated by multiplying the change in number of crashes of each severity level by the average costs of each crash (Rodegerdts 2010).

As reviewed earlier, roundabouts reduce crashes compared with stop-controlled or signalized intersections. Table 1 presents an estimate of average economic costs on a per accident basis for each severity level for the year 2000 available from the American Association of State Highway and Transportation Officials (AASHTO 2010b). Estimates for 2014, which were based on values for 2000, and updated from 2000 to 2014 based on the change in the value of a statistical life reported for 2000 (Blincoe et al. 2000) and 2014 (Rogoff and Thomson 2014). There has been a sharp increase in the measured value of a statistical life from $3.4 million in 2000 to $9.4 million in 2014.

Table 1: Average Comprehensive Cost of Motor-Vehicle Crashes by Injury Severity, 2000 and 2014

Severity	Economic Cost Per Accident (2000 Dollars)*	Economic Cost Per Accident (2014 Dollars)
Fatal	$3,753,200	$10,480,100
Non-Fatal Injury	$138,100	$385,600
Property Damage Only	$3,900	$10,900
All Injury	$202,300	$567,700

* Source: AASHTO 2010b

The Office of Management and Budget issued significant upward revisions to its recommended Value of a Statistical Life in both 2008 and 2012 to reflect advancements in the economics literature. The 2008 revision to $5.8 million was made due to: 1) the introduction of the growth in real wages as a factor in updating estimates and 2) the substitution of the consumer price index for the GDP deflator when updating estimates (Szabat and Knapp 2009). The 2012 revision utilized improved estimates for the Value of a Statistical Life based on studies using the newly available Census of Fatal Occupational Injuries produced by the United States Bureau of Labor Statistics. The result was an increase in the recommended Value of Statistical Life from $6.2 million in 2011 to $9.1 million in 2012 (Trottenberg and Rivkin 2013).

The reviewed literature showed that roundabouts are mostly safer than stop-controlled or signalized intersections in terms of total crash frequencies, especially injury crash frequencies. Roundabouts converted from stop-controlled or signalized intersections with high-speed approaches in rural and suburban areas seem to have greater crash reductions than roundabouts in low-speed

urban settings (Persaud et al. 2001; Antoine 2005; Rodegerdts 2007). With a significant reduction in crash frequency and severities, substantial safety benefits of the conversion can be expected. However, more research work is still needed before we draw the conclusion that roundabouts are the most appropriate and cost-effective control for intersections with high-speed approaches in rural settings. This study therefore explored the safety performance and its corresponding economic values of roundabouts with high-speed approaches in rural settings using data obtained from Kansas; the studied roundabouts were all TWSC intersections before conversion.

MODELING BACKGROUND

The EB before-after safety evaluation method uses safety performance functions (SPFs) to estimate what the expected average crash frequency would have been at a location where a safety improvement treatment was implemented, had the treatment not been implemented. The expected average crash frequency can be denoted as $N_{expected,After}$ or simply $N_{expected,A}$, which stands for the expected crash frequency for the after period assuming the treatment was not applied and the location remained the same as before. It then compares the actual observed crashes after the treatment application, which is denoted as $N_{observed,After}$ or simply $N_{observed,A}$, to the expected average if the treatment had not been applied, $N_{expected,A}$, to determine the treatment's safety effectiveness (AASHTO 2010a).

The fluctuation of crashes over time at a location makes it difficult to determine whether the crash frequency changes are due to a safety treatment or are due to the natural fluctuation. When a site experiences high (low) crash frequency in a certain period, it is statistically probable that it will experience a comparatively low (high) crash frequency in the following period of similar duration. This phenomenon is known as regression-to-the-mean (RTM). Compared with simple before-after analysis, EB results are adjusted by changes in traffic volumes and corrected for potential biases from the RTM effect. The EB method is used in the *Highway Safety Manual* (AASHTO 2010a); the procedures are described as follows.

The predicted average crash frequency for a year, $N_{predicted}$, is expressed as per intersection per year.

(1) $N_{predicted} = N_{spfx} \times (CMF_{1x} \times CMF_{2x} \times \ldots \times CMF_{yx}) \times C_x$

Where N_{spfx} = predicted average crash frequency determined for base condition of the SPF developed for site type x,

CMF_{yx} = crash modification factors specific to SPF for site type x, and

C_x = calibration factor to adjust SPF for local conditions for site type x.

The expected average crash frequency for the before treatment period is expressed as per intersection summed for the entire before period.

(2) $N_{expected,B} = w_{i,B} N_{predicted,B} + (1 - w_{i,B}) N_{observed,B}$

Where, the weight for each site i is determined as:

(3) $w_{i,B} = 1 / (1 + k \sum_{Before\ years} N_{predicted})$

$N_{expected,B}$ = expected average crash frequency at site i for the entire before treatment period,

$N_{observed,B}$ = observed crash frequency at site i for the entire before treatment period, and

k = over-dispersion parameter for the applicable SPF.

The predicted average crash frequency for each site *i* during each year of the after treatment period can be calculated in the same way. The adjustment factor, r_i, which accounts for the difference between the before and after treatment periods in duration and traffic volume at each site *i* is:

(4) $r_i = (\sum_{After\ years} N_{predicted,A}) / (\sum_{Before\ years} N_{predicted,B})$

The expected average crash frequency for each site *i* over the entire after period in the absence of the treatment is:

(5) $N_{expected,A} = N_{expected,B} \times r_i$

The estimate of the safety effectiveness of the treatment at site *i* can be expressed in the form of an odds ratio,

(6) $OR_i = N_{observed,A} / N_{expected,A}$

The percentage crash change at site *i* is:

(7) $P_i = 100 \times (1 - OR_i)$

The overall effectiveness of the treatment for all sites combined, in the form of an odds ratio, is expressed as:

(8) $OR' = (\sum_{All\ sites} N_{observed,A}) / (\sum_{All\ sites} N_{expected,A})$

The odds ratio above is potentially biased. In statistics, this is called the bias for the ratio estimator. It can be shown with Jensen's inequality as

(9) $E(X/Y) = E[X\ (1/Y)] = E(X)\ E(1/Y) \geq E(X) \times [1/E(Y)] = E(X)/E(Y)$

The inequality is because the equal deviations of *y* below and above *E(Y)* exert unequal influence on the ratio *1/y*. For example, suppose that the random variable *Y* takes on the values of *y* = 0.5 and *y* = 1.5 with equal probability so *E(Y)* = 0.5*(0.5+1.5) = 1.0 while *E(1/Y)* = 0.5*(1/0.5+1/1.5) = 1.33, which is not *1/E(Y)* = 1.0 (Hauer 1997).

An unbiased estimate of the overall effectiveness is:

(10) $OR = OR' / [1 + Var\ (\sum_{All\ sites} N_{expected,A}) / (\sum_{All\ sites} N_{expected,A})^2\ ]$

In which, $Var(\sum_{All\ sites} N_{expected,A}) = \sum_{All\ sites} [(r_i)^2 \times N_{expected,B} \times (1 - w_{i,B})]$.

EB BEFORE-AFTER CRASH ANALYSIS

Crash and Traffic Data

Crash data on four rural high-speed (45-65 mph) intersections with two-way stop control that were converted to roundabouts were obtained from the Kansas Department of Transportation (KDOT). The period when two-way stop control was in effect was referred to as the "before" time period

(i.e., before conversion to roundabouts) while the roundabout period was termed as the "after" period; conversion to roundabout was the safety treatment in each case. Crashes reported during the conversion year were excluded to remove any construction effects. Information for fatal, injury, and property-damage-only (PDO) crashes for each year in the before and after periods was utilized in the analysis. Table 2 presents the locations of the four roundabouts, the crash counts in the two time periods, and annual average daily traffic (AADT) before and after roundabout conversion. Due to the availability of the crash data, varied lengths of years were applied in the before and after time periods. For example, for the site US-400 & K-47, crash data for five years before the conversion (2004-2008) and data for three years after (2010-2012) were used. Data for 2009 were excluded since 2009 was the construction year. Notice that the application of different lengths of years would not affect the conclusion because the EB method already takes into account the changes of years when calculating the expected crashes for the after period.

The AADT information was collected from a KDOT historical state traffic flow map. In some instances, AADT on the corresponding major road legs were different, in which case the larger of the two values was recorded as the AADT for the major road (AADTmaj), consistent with the guidance in the *Highway Safety Manual* (AASHTO 2010a). The AADT on the minor roads (AADTmin) were determined in a similar manner. Traffic volumes did not change significantly after conversion of the TWSC intersections to roundabouts except for the US-400 & K-47 intersection. For the US-400 & K-47 intersection, AADT on major and minor approaches were decreased by 11% and 25%, respectively. For the other three sites, changes of AADT on major and minor approaches were less than 10%. Traffic volumes for the four sites ranged from 2,000 to 7,000 vehicles/day. Annual average crash rates before conversion were from 4.2 to 5.0 accidents/year.

While the characteristics of these four TWSCs that were converted to roundabouts may not represent all TWSC intersections in the U.S. with respect to traffic volumes and number of crashes, they should be representative of TWSCs that have comparable crash histories and traffic volumes.

EB Before-After Analysis

Table 3 presents the results of the EB before-after analysis for total, fatal, non-fatal injury, and PDO crashes reported at each site. The odds ratios (column 5) were calculated by dividing observed number of crashes by expected number of crashes; a value smaller than 1.00 indicates that a particular location experienced fewer crashes after conversion to roundabouts. Percentage reductions (column 6) represent crash reduction rates; larger values represent greater crash reductions. The intersection at US-400 & K-47 experienced an increase in total crashes after conversion (from an expected total of 8.03 to an actual observed total of nine crashes within three years), a 100% decrease in fatal crashes (from an expected value of 0.17 to an actual observed of zero fatal crashes), and a slight decrease in injury crashes (from an expected value of 4.26 to an actual observed of four non-fatal injury crashes). The other three locations had a significant percentage reduction ranging from 45% to 84% for total crashes, 100% for fatal crashes, and from 80% to 100% for injury crashes. The results for the PDO crashes, however, were mixed as two locations (US-400 & K-47, from 3.6 to 5.0; US-50 & US-77, from 6.3 to 7.0) experienced an increase in such crashes.

Table 4 presents the results of aggregated analysis of all four locations, i.e., crashes at all locations in each time period were pooled for the analysis. The overall effectiveness of the treatment (conversion to roundabouts) for all sites combined can be expressed in the form of an odds ratio (column 5). This odds ratio is potentially biased, but an unbiased estimate of the overall effectiveness is presented in column 6. Overall, all types of crashes were reduced after conversion to roundabouts. Total crashes were reduced by 58.13%; fatal crashes were reduced by 100%; injury crashes were reduced by 76.47%; while PDO crashes were reduced by 35.49%. The results are mostly consistent with studies reported in the literature.

Table 2: Information on the Four Intersections/Roundabouts*

Intersecting Roads	Conversion Year	Number of Legs	Before Period					After Period					Posted Speed
			Years	Total Crashes	Fatal and Injury Crashes	AADTmaj/ truck %	AADTmin/ truck %	Years	Total Crashes	Fatal and Injury Crashes	AADTmaj / truck %	AADTmin/ truck %	Major/Minor (mph)
US-400 & K-47	2009	4	2004-2008	21	13	4116 /22%	3004 /10%	2010-2012	9	4	3673 /24%	2250 /13%	65/65
US-400/US-69A & K-66	2008	4	2003-2006	19	10	6818 /9%	4940 /6%	2009-2012	3	0	6730 /9%	4923 /7%	65/45
E. Jct. of US-77 & US-166	2009	4	2004-2008	21	11	5036 /13%	4192 /15%	2010-2012	3	1	5493 /12%	4157 /12%	65/55
US-50 & US-77	2006	5	2001-2004	20	14	3545 /48%	2190 /11%	2007-2010	9	2	3370 /49%	2028/ 16%	55/45

* Source: Kansas Department of Transportation (KDOT)

Table 3: Empirical Bayes Analysis of All Crashes

Intersecting Roads	Observed Total Crashes (Before)	Observed Total Crashes (After)	Expected Total Crashes (After)	Odds Ratio (Observed/Expected, After)	Percentage Reduction % [100*(1-Odds Ratio)]
Total Crashes					
US-400 & K-47	21.00	9.00	8.03	1.12	-12.10
US-400/US-69A & K-66	19.00	3.00	19.34	0.16	84.48
E. Jct. of US-77 & US-166	21.00	3.00	13.64	0.22	78.01
US-50 & US-77	20.00	9.00	16.31	0.55	44.81
Fatal Crashes					
US-400 & K-47	3.00	0.00	0.17	0.00	100.00
US-400/US-69A & K-66	0.00	0.00	0.40	0.00	100.00
E. Jct. of US-77 & US-166	0.00	0.00	0.25	0.00	100.00
US-50 & US-77	3.00	0.00	0.40	0.00	100.00
Non-fatal Injury Crashes					
US-400 & K-47	10.00	4.00	4.26	0.94	6.15
US-400/US-69A & K-66	10.00	0.00	9.31	0.00	100.00
E. Jct. of US-77 & US-166	11.00	1.00	6.57	0.15	84.78
US-50 & US-77	11.00	2.00	9.60	0.21	79.17
Property-damage-only (PDO) Crashes					
US-400 & K-47	8.00	5.00	3.60	1.39	-38.89
US-400/US-69A & K-66	9.00	3.00	9.63	0.31	68.85
E. Jct. of US-77 & US-166	10.00	2.00	6.82	0.29	70.67
US-50 & US-77	6.00	7.00	6.30	1.11	-11.11

Table 4: Empirical Bayes Before-After Analysis for All Locations (Aggregated)

Crash Type	Observed Crashes (After)	Expected Crashes (After)	Percentage Change %	Odds Ratio	Unbiased Odds Ratio
Total	24.00	57.31	58.13	0.42	0.41
Fatal	0.00	1.22	100.00	0.00	0.00
Injury	7.00	29.74	76.47	0.24	0.23
Property-damage-only	17.00	26.35	35.49	0.65	0.63

The following assumptions were made in the EB analysis:

1. The TWSC intersections did not have any significant skew.
2. Except for the US-400 & K-47 intersection, the remaining three intersections had no left-turn lanes and no lighting during the before time period (the US-400 & K-47 intersection showed a left-turn lane on each major approach as well as lighting before conversion on Google Map Street View, imagery captured in November 2007).
3. All intersections were assumed to have no right-turn lanes and the local calibration factors (Cs) were assumed equal to 1.0.

Before-After Analysis of Fatalities and Injuries in Crashes

Table 5 presents the before-after analysis of fatality and injury rates at the four locations. Fatality and injury rates (on a per-year base) in all four locations were reduced after conversions to roundabouts. Fatality rates were reduced by 100% while injury rates were reduced by at least 60%. The analysis showed that severe crashes significantly decreased after the TWSC intersections were converted to roundabouts.

ECONOMIC EVALUATION – SAFETY BENEFIT

An important and a major component of the economic analysis is the avoided cost of crashes. Analysis in Tables 3 through 5 revealed a significant decline in crashes after conversion of the TWSC intersections on rural, high-speed roads to roundabouts at the four sites as a group. In particular, the number of crashes in the years after roundabout completion was well below expected crashes, based on crash rates in the periods before conversions to roundabouts. The decline was particularly pronounced among injury crashes, suggesting that the conversion to roundabouts was reducing both the number and severity of crashes. Such a change would generate significant economic value in terms of safety benefits. These benefits are estimated based on values presented in Table 1 and shown in Table 6.

The total value of the estimated 33.3 avoided crashes was $21.7 million. The value is large because the conversion to a roundabout helped reduce the severity as well as the number of crashes. For example, more than half of this amount, $12.8 million, resulted from avoiding 1.2 fatal crashes. The 33.3 avoided crashes were avoided at the four roundabouts over a three- or four-year post-roundabout construction period. Notice that the post-period crash data were collected for four years each at two of the intersections and for three years each at the other two intersections, resulting in a total of 14 year-intersections. Thus, the annual value of reduced crashes at a single intersection would be one-fourteenth as much, or $1.6 million ($21.7 million saved in total /14 year-intersections= $1.6 million per year per intersection). Considering the initial construction cost for one roundabout is around $3.0 million (according to Church 2007) (the construction costs for the US-50 & US-77

Table 5: Before-After Analysis of Death and Injury Rates (Per Year)

Location	Death Rate (Before)	Injury Rate (Before)	Death Rate (After)	Injury Rate (After)	Death Rate Change %	Injury Rate Change %
US-400 & K-47	0.60	5.80	0.00	2.33	-100.00	-59.77
US-400/US-69A & K-66	0.00	4.75	0.00	0.00	-	-100.00
E. Jct. of US-77 & US-166	0.00	5.00	0.00	0.33	-	-93.33
US-50 & US-77	1.00	7.00	0.00	0.50	-100.00	-92.86
All Sites	0.39	5.61	0.00	0.71	-100.00	-87.27

Table 6: Value of Avoided Comprehensive Crash Costs Over 3-4 Years

Crash Type	Observed Crashes (After)	Expected Crashes (After)	Reduction in Crashes	Comprehensive Crash Cost 2014	Crash Costs Avoided*
All Crashes	24.00	57.31	33.31	-	-
Fatal	0.00	1.22	1.22	$10,480,100	$12,785,700
Injury (Non-Fatal)	7.00	29.74	22.74	$385,600	$8,769,000
Property-damage-only	17.00	26.35	9.35	$10,900	$101,800
Total (4 intersections over 3-4 years)					$21,656,500

* The results of these economic estimates were based on the estimate of average economic costs on a per accident basis for each severity level for the year 2014, as shown in Table 1.

roundabout was $3.2 million; construction costs for another two similar roundabouts in Kansas that were not included in our study were $2.4 and $2.5 million), the savings of $1.6 million per year per intersection due to avoided crashes were significant. This result, however, depends to a significant degree on avoided fatal crashes at the roundabout. Six fatal crashes were reported at the TWSC intersections in the years before they were converted to roundabouts but none reported afterwards. Given the small number of intersections and fatal crashes involved, and comprehensive crash costs in excess of $10 million for each fatal crash, it is natural to wonder how much happenstance influenced the results. In particular, severe crashes may have occurred both before and after installation of the roundabout, but none were fatal after the roundabout was in use. This may reflect the relative safety of roundabouts but also may simply reflect chance. To address the latter possibility, Table 6 was revised by summing the fatal and non-fatal injury crashes to create a category for all injury crashes (fatal and non-fatal). The lower comprehensive crash cost in 2014 ($567,700, which was based on the value for 2000 and updated from 2000 to 2014 based on the change in the value of a statistical life, as shown in the last row of Table 1) for all injury crashes was utilized; Table 7 shows the results.

Table 7: Value of Avoided Comprehensive Crash Costs over 3-4 Years With Fatal and Non-Fatal Injury Crashes Combined

Crash Type	Observed Crashes (After)	Expected Crashes (After)	Reduction in Crashes	Comprehensive Crash Cost 2014	Crash Costs Avoided
All Crashes	24.00	57.31	33.31	-	-
Injury (Fatal and Non-Fatal)	7.00	30.96	23.96	$567,700	$13,601,500
Property-damage-only	17.00	26.35	9.35	$10,900	$101,800
Total (4 intersections over 3-4 years)					$13,703,400

The total estimated value from the 33.3 avoided crashes was $13.7 million. This translated into avoided crash costs of $1.0 million per year at each intersection ($13.7 million saved in total /14 year-intersections = $1.0 million per year per intersection). Therefore, the estimate of the annual reduction in comprehensive crash costs from conversion of TWSC intersections to roundabouts on rural high-speed roads was between $1.0 million and $1.6 million in 2014 dollars. Assuming a 20-year lifespan for a roundabout (based on FHWA 2010), the estimated monetary benefits due to avoided crashes were between $20.0 million and $32.0 million.

When interpreting these results, it is important to remember that safety benefits are just one of the components of economic benefits that can result from a transportation investment. The conversion of TWSC intersections to roundabouts could also result in a change in user costs such as travel time and vehicle operating costs and non-user costs such as vehicle emissions. The change in these costs would need to be included along with the estimated safety benefits in order to estimate comprehensive annual economic benefits from a roundabout intersection. Only such comprehensive annual benefits can be compared with costs as part of a benefit and cost analysis.

CONCLUSION AND DISCUSSION

Modern roundabouts provide an alternative to stop-controlled or signalized intersections; conversions of existing intersections to roundabouts continue across the U.S. While the safety benefits of converting traditionally controlled intersections to modern roundabouts in urban settings have been well-documented, conversions of TWSC intersections on rural, high-speed roadways to modern roundabouts have not been explored to the same extent. This study focused on the assessment of four rural high-speed approach TWSC intersections that were converted to roundabouts in Kansas. The evaluation procedures utilized were from the *Highway Safety Manual* (AASHTO 2010a). Economic evaluation was carried out to assess the monetary value of the safety benefits acquired.

Results of the analysis showed that, overall, all types of crashes were reduced after conversion of TWSC intersections to roundabouts. Total crashes decreased by 58.13%; fatal crashes were reduced by 100% at all locations; and non-fatal injury crashes were reduced with an overall reduction rate of 76.47%. Property-damage-only crashes were reduced by 35.49% as a whole, but two out of the four sites experienced increases in property-damage-only crashes after conversion to roundabouts. Based on the before-after analysis, fatality and injury rates were decreased at all four sites. In conclusion, the answer to the question "Are roundabouts on rural high-speed roadways safer than TWSC intersections?" is affirmative in our case, and that conversion of TWSC rural high-speed intersections to roundabouts provided similar safety benefits as their urban counterparts. The conclusions are consistent with previous studies on rural high-speed roundabouts.

Finally, to answer the question "What economic benefits can be expected for the conversion from TWSC intersections to roundabouts in terms of safety improvement?" the estimated safety benefits were significant in monetary terms. As in our case, the annual value of the reduction in comprehensive crash costs from conversion of a TWSC intersection on a rural, high-speed roadway to a modern roundabout was between $1.0 million and $1.6 million in 2014 dollars. Although it is too early to generalize this conclusion to all TWSC intersections, it should be reasonable for analysts and decision makers to expect parallel monetary benefits from converting rural high-speed approach TWSC intersections with similar traffic conditions and crash histories to modern roundabouts.

Although this paper accomplished its objectives of evaluating the safety benefits of rural roundabouts with high-speed approaches, the analysis is limited to the four intersections included in this study. The four sites may not be representative of all TWSC intersections in the U.S. with respect to traffic volumes and number of crashes. However, they should be representative of TWSC intersections with similar crash and traffic histories, design features, and driving behaviors. Studies based on larger datasets that include more qualified rural high-speed intersections are needed in the future to further testify to the safety performance of such roundabouts. On the other hand, for the safety benefit evaluation, the analysis relies on the average severity of non-fatal injury crashes that was utilized in AASHTO (2010b). A more precise estimate of safety benefits could consider the specific severity of non-fatal injury crashes reported at roundabouts and two-way-stop-controlled intersections. The severity might be expected to differ, particularly in light of the lesser severity of crashes in roundabouts observed in Table 4.

Acknowledgements

The authors would like to acknowledge the Nebraska Department of Roads (NDOR) for funding the research. NDOR staff members Ryan Huff, Dan Waddle, Matt Neeman, Phil TenHulzen, Nathan Sorben, Jodi Gibson, and Anna Rea helped with various aspects of the research and provided valuable insights. The authors are thankful for the assistance received from Kansas DOT staff including Rex McCommon, Michael Guerrero, Theresa Havenstein, and Cheryl Lambrecht.

References

American Association of State Highway and Transportation Officials (AASHTO). *Highway Safety Manual.* Washington, D.C., 2010a.

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

Antoine, D. "The Safety of Roundabouts and Traffic Lights in Belgium." *Transportation Research Circular 2005*, E-C083, (2005): 20-20.

Appleton, I. and G. Clark. *The Ins and Outs of Roundabouts*. Traffic Design Group, New Zealand, 1998.

Blincoe, L., A. Seay, E. Zaloshnja, T. Miller, E. Romano, S. Luchter, and R. Spicer. *The Economic Impact of Motor Vehicle Crashes*. U.S. DOT, Washington, D.C., 2000.

Church, D. "Kansas - High Speed Approach Roundabouts Rural Roundabouts." Presentation, MoDOT State Traffic & Safety Conference, May 11, 2007.

Cunningham, R. "*Maryland's Roundabouts: Accident Experience and Economic Evaluation.*" Maryland State Highway Administration, Office of Traffic and Safety, 2007.

Federal Highway Administration (FHWA). "*Roundabouts – The Maryland Experience. A Maryland Success Story.*" Office of Traffic and Safety, 2010.

Flannery, A. and T.K. Datta. "Modern Roundabouts and Traffic Crash Experience in United States." *Transportation Research Record: Journal of the Transportation Research Board* 1553(1), (1996) 103-109.

Hauer, Ezra. *Observational Before/After Studies in Road Safety. Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety*. Pergamon, Oxford, OX, U.K. (1997): 64-65.

Isebrands, H. and S. Hallmark. "Statistical Analysis and Development of Crash Prediction Model for Roundabouts on High-Speed Rural Roadways." *Transportation Research Record: Journal of the Transportation Research Board* 2312(1), (2012): 3–13.

Lanani, N. "Roundabout Impacts on Accidents." *Greater London Intelligence Quarterly* 32, (1975): 31-36.

Mandavilli, S., A.T. McCartt, and R.A. Retting. "Crash Patterns and Potential Engineering Countermeasures at Maryland Roundabouts." *Traffic Injury Prevention*, 10(1), (2009): 44-50.

Maycock, G. and R.D. Hall. "Accidents at 4-arm Roundabouts." *Transportation Research Record: Journal of the Transportation Research Board* 249. No. MONOGRAPH, 1984.

Myers, E.J. "Accident Reduction with Roundabouts." *Transportation Frontiers for the Next Millennium: 69th Annual Meeting of the Institute of Transportation Engineers*, No. CD-006, 1999.

Nebraska Department of Roads. "Intersections, Driveways and Channelization." *Roadway Design Manual, 4–54*. Nebraska Department of Roads, 2012.

Persaud, B.N., R.A. Retting, P.E. Garder, and D. Lord. *Crash Reductions Following Installation of Roundabouts in the United States*. Arlington, USA: Insurance Institute for Highway Safety, 2000.

Persaud, B., R. Retting, P. Garder, and D. Lord. "Observational Before-After Study of the Safety Effect of US Roundabout Conversions Using the Empirical Bayes Method." *Transportation Research Record: Journal of the Transportation Research Board* 1751(1), (2001): 1-8.

Qin, X., A. Bill, M. Chitturi, and D. Noyce. "Evaluation of Roundabout Safety." *Transportation Research Board 92nd Annual Meeting Compendium Papers* No. 13-2060, 2013.

Ritchie, S. and M. Lenters. "High Speed Approaches at Roundabouts." *Transportation Research Circular E-C083*, (2005): 56-56.

Rogoff, P. and K. Thomson. *Guidance on Treatment of the Economic Value of a Statistical Life (VSL) in U.S. Department of Transportation Analyses,* U.S. Department of Transportation Memorandum, June 2014.

Rodegerdts, Lee. "Safety Findings." *Transportation Research Board NCHRP Report* 572: *Roundabouts in the United States*, (2007): 23 -33.

Rodegerdts, L. A. "Safety." *Transportation Research Board NCHRP Report* 672: *Roundabouts: An Informational Guide*, (2010): 1-35.

Szabat, J. and L. Knapp. *Guidance on Treatment of the Economic Value of a Statistical Life (VSL) in U.S. Department of Transportation Analyses – 2009 Annual Revision*. Department of Transportation Memorandum, March 18, 2009.

Thomas, G. and A. Nicholson. "Rural Roundabouts and Their Application in New Zealand." *Institution of Professional Engineers New Zealand (IPENZ) Transportation Group*, *Technical Conference Papers*, 2003.

Trottenberg, P. and R. Rivkin. *Guidance on Treatment of the Economic Value of a Statistical Life (VSL) in U.S. Department of Transportation Analyses.* Department of Transportation Memorandum, February 28, 2013.

Tudge, R. "Accidents at Roundabouts in New South Wales." *Australian Road Research Board (ARRB) Conference*, *Darwin, Northern Territory*, 15(5), (1990): 331-349.

Shanshan Zhao *is currently a Ph.D. student in the Department of Civil Engineering at the University of Nebraska-Lincoln. She obtained her M.Sc. in transportation engineering from Tongji University in 2012. Her research interest is in highway safety and freight transportation.*

Aemal J. Khattak *is currently an associate professor in the Department of Civil Engineering at the University of Nebraska-Lincoln. He specializes in highway safety and teaches both undergraduate and graduate courses in transportation engineering.*

Eric C. Thompson *is an associate professor of economics and the director of the Bureau of Business Research at the University of Nebraska-Lincoln. His research examines competitive factors affecting state and local economic growth, the impact of infrastructure on the economy, and the role of entrepreneurship in regional economic development.*

Transportation Research Forum

Statement of Purpose

The Transportation Research Forum is an independent organization of transportation professionals. Its purpose is to provide an impartial meeting ground for carriers, shippers, government officials, consultants, university researchers, suppliers, and others seeking an exchange of information and ideas related to both passenger and freight transportation. The Forum provides pertinent and timely information to those who conduct research and those who use and benefit from research.

The exchange of information and ideas is accomplished through international, national, and local TRF meetings and by publication of professional papers related to numerous transportation topics.

The TRF encompasses all modes of transport and the entire range of disciplines relevant to transportation, including:

Economics	Urban Transportation and Planning
Marketing and Pricing	Government Policy
Financial Controls and Analysis	Equipment Supply
Labor and Employee Relations	Regulation
Carrier Management	Safety
Organization and Planning	Environment and Energy
Technology and Engineering	Intermodal Transportation
Transportation and Supply Chain Management	

History and Organization

A small group of transportation researchers in New York started the Transportation Research Forum in March 1958. Monthly luncheon meetings were established at that time and still continue. The first organizing meeting of the American Transportation Research Forum was held in St. Louis, Missouri, in December 1960. The New York Transportation Research Forum sponsored the meeting and became the founding chapter of the ATRF. The Lake Erie, Washington D.C., and Chicago chapters were organized soon after and were later joined by chapters in other cities around the United States. TRF currently has about 300 members.

With the expansion of the organization in Canada, the name was shortened to Transportation Research Forum. The Canadian Transportation Forum now has approximately 300 members.

TRF organizations have also been established in Australia and Israel. In addition, an International Chapter was organized for TRF members interested particularly in international transportation and transportation in countries other than the United States and Canada.

Interest in specific transportation-related areas has recently encouraged some members of TRF to form other special interest chapters, which do not have geographical boundaries – Agricultural and Rural Transportation, High-Speed Ground Transportation, and Aviation. TRF members may belong to as many geographical and special interest chapters as they wish.

A student membership category is provided for undergraduate and graduate students who are interested in the field of transportation. Student members receive the same publications and services as other TRF members.

Annual Meetings

In addition to monthly meetings of the local chapters, national meetings have been held every year since TRF's first meeting in 1960. Annual meetings generally last three days with 25 to 35 sessions. They are held in various locations in the United States and Canada, usually in the spring. The Canadian TRF also holds an annual meeting, usually in the spring.

Each year at its annual meeting the TRF presents an award for the best graduate student paper. Recognition is also given by TRF annually to an individual for Distinguished Transportation Research and to the best paper in agriculture and rural transportation.

Annual TRF meetings generally include the following features:

- Members are addressed by prominent speakers from government, industry, and academia.
- Speakers typically summarize (not read) their papers, then discuss the principal points with the members.
- Members are encouraged to participate actively in any session; sufficient time is allotted for discussion of each paper.
- Some sessions are organized as debates or panel discussions.

Past Presidents

2014	Art Guzzetti
2013	Jack Ventura
2012	Ken Button
2011	Alan R. Bender
2010	B. Starr McMullen
2009	Richard Gritta
2008	Kenneth Button
2007	John (Jack) V. Wells
2006	Anthony M. Pagano
2005	Scott E. Tarry
2004	John S. Strong
2003	C. Gregory Bereskin
2002	Martin Dresner
2001	Mark R. Dayton
2000	Richard S. Golaszewski
1999	Aaron J. Gellman
1998	Richard Beilock
1997	Robert Harrison
1996	Clinton V. Oster, Jr.
1995	Paul K. Gessner
1994	Russell B. Capelle, Jr.
1993	Louis A. LeBlanc
1992	Stephen J. Thompson
1991	Joanne F. Casey
1990	Frederick J. Beier
1989	Thomas N. Harvey
1988	Joedy W. Cambridge
1987	Frederick C. Dunbar
1986	Carl D. Martland
1985	Allan D. Schuster
1984	Douglas McKelvey
1983	William B. Tye
1982	Michael S. Bronzini
1981	Jay A. Smith, Jr.
1980	Samual E. Eastman
1979	Lana R. Batts
1978	Carl J. Liba
1977	Gerald Kraft
1976	Edward Morlok
1975	Barry A. Brune
1974	Richard Shackson
1973	Harvey M. Romoff
1972	Arthur Todd
1971	Herbert E. Bixler
1970	Paul H. Banner
1969	George W. Wilson
1968	Donald P. MacKinnon
1967	David L. Glickman
1966	Edward Margolin
1965	Robert A. Bandeen
1964	Gayton Germane
1963	Herbert O. Whitten
1962	Herbert O. Whitten
1961	Herbert O. Whitten
1960	Herbert O. Whitten
1959	John Ingram (TRF of NY)
1958	Herbert O. Whitten (TRF of NY)

Recipients of the TRF Distinguished Transportation Researcher Award

2015	Allen D. Biehler
2014	Joseph M. Sussman
2013	Wayne K. Talley
2012	Genevieve Giuliano
2011	Martin Wachs
2010	Clifford Winston
2009	Daniel McFadden
2008	Steven A. Morrison
2007	José A. Gomez-Ibanez
2006	Tae H. Oum
2005	Kenneth Button
2004	Kenneth Small
2000	Michael E. Levine
1998	Edward K. Morlok
1997	Carl D. Martland
1996	Benjamin J. Allen
1995	D. Philip Locklin
1994	Martin T. Farris
1993	C. Phillip Baumel
1992	Alan A. Altshuler
1990	George W. Wilson, Ph.D.
1989	Sir Alan Arthur Walters, B. Sci., Hon. D. Soc. Sci.
1988	Karl M. Ruppenthal, Ph.D.
1987	William S. Vickrey, Ph.D.
1986	William J. Harris, D. Sci., Hon. D. Eng.
1985	John R. Meyer, Ph.D.
1984	Alfred E. Kahn, Ph.D.
1982	W. Edwards Deming, Ph.D.
1979	James C. Nelson, Ph.D.
1978	James R. Nelson, Ph.D.
1977	Lewis K. Sillcox, D. Sci., D. Eng., LL.D., D.H.L.

Recipients of the Herbert O. Whitten TRF Service Award

2015	Ian Savage
2014	Kenneth Button
2013	B. Starr McMullen
2012	Kofi Obeng
2011	Anthony Pagano
2010	Captain James R. Carman
2009	John (Jack) Wells
2008	Gordon MacDougall
2007	Robert T. Beard
2006	Gene C. Griffin
2005	Michael W. Babcock
2004	Jack S. Ventura
2000	Paul K. Gessner
1998	Arthur W. Todd
1996	Stephen J. Thompson
1994	Samuel Ewer Eastman
1991	Carl D. Martland, C.E.
1990	Herbert O. Whitten, M.B.A.

Past Editors of JTRF

Kofi Obeng (2005-2014)
Wayne K. Talley (1998-2000)
K. Eric Wolfe (1993-1998)
Kevin H. Horn (1993-1998)
Anthony M. Pagano (1987-1993)
Richard Beilock (1987-1993)

Recipients of the TRF Best Paper Award

2015 Chen (Sarah) Xu and Liang-Chieh (Victor) Cheng, *Accounting for Natural Gas Vehicles in Regional Auto Markets–Estimates for the State of Texas, U.S.*

2014 Ju Dong Park and Won W. Koo, *The Magnitudes of Economic and Non-Economic Factors in Demand for U.S. Domestic Air Passengers*

2013 Carl Martland, *Introduction of Heavy Axle Loads by the North American Rail Industry, 1990 to 2012*

2012 Rafael Costa & C. Parr Rosson, III, *The Impacts of the Panama Canal Expansion on World Cotton Trade*

2011 Alexander Bigazzi and Miguel Figliozzi, *A Model and Case Study of the Impacts of Stochastic Capacity on Freeway Traffic Flow and Benefits Costs*

2010 Tony Diana, *Predicting Arrival Delays: An Application of Spatial Analysis*

2009 Tae H. Oum, Jia Yan, and Chunyan Yu, *Ownership Forms Matter for Airport Efficiency: A Stochastic Frontier Investigation of Worldwide Airports*

2008 C. Gregory Bereskin, *Railroad Cost Curves Over Thirty Years – What Can They Tell Us?*

2007 Rob Konings, Ben-Jaap Pielage, Johan Visser, Bart Wiegmans, *"Container Ports and Their Hinterland: Multimodal Access and Satellite Terminals within the Extended Gateway Concept"*

2006 Ian Savage, *Trespassing on the Railroad.*

2005 Patrick DeCorla-Souza, *A New Public-Private Partnership Model for Road Pricing Implementation.*

2004 Ian Savage and Shannon Mok, *Why Has Safety Improved at Rail-Highway Crossings*?

2000 Ian Savage, *Management Objectives and the Causes of Mass Transportation.*

1999 C. Phillip Baumel, Jean-Philippe Gervais, Marty J. McVey, and Takehiro Misawa, *Evaluating the Logistics Economic Impacts of Extending Six Hundred Foot Locks on the Upper Mississippi River: A Linear Programming Approach*.

1998 Carl Scheraga and Patricia M. Poli, *Assessing the Relative Efficiency and Quality of Motor Carrier Maintenance Strategies: An Application of Data Entry Envelopment Analysis*.

1997 Wayne K. Talley and Ann Schwarz-Miller, *Motor Bus Deregulation and Racial/Gender Effects: Earnings and Employment*.

1996 Todd Litman, *Full Cost Accounting for Transportation Decision Making: Estimates, Implications and Applications*.

1995 Leon N. Moses and Ian Savage, *A Cost-Benefit Analysis of United States Motor Carrier Safety Programs*.

1994 Brian Shaffer and James Freeman, *Variation in Producer Responses to Automobile Fuel Economy Mandates*.

1993 W. Bruce Allen and Dong Liu, *Service Quality and Motor Carrier Costs: An Empirical Analysis*.

1992 Victor E. Eusebio, Stephen J. Rindom, Ali Abderrezak, and John Jay Rosacker, *Rail Branch Lines at Risk: An Application of the Exponential Survival Model on Kansas Duration Data*.

1991 Patrick Little, Joseph M. Sussman, and Carl Martland, *Alternative Freight Car Maintenance Policies with Attractive Reliability/Cost Relationships*.

1990 James A. Kling, Curtis M. Grimm, and Thomas M. Corsi, *Strategies of Challenging Airlines at Hub-Dominated Airports*.

1989 Cathy A. Hamlett, Sherry Brennan, and C. Phillip Baumel, *Local Rural Roads: A Policy Analysis*.

1988 John R. Brander, B. A. Cook, and John Rowcroft, *Auctioning Runway Slots: Long Term Implications.*

1987 Clinton V. Oster, Jr. and C. Kurt Zorn, *Deregulation's Impact on Airline Safety.*

1986 Chulam Sarwar and Dale G. Anderson, *Impact of the Staggers Act on Variability and Uncertainty of Farm Product Prices*.

1985 Brian D. Adam and Dale G. Anderson, *Implications of the Staggers Rail Act of 1980 for Level and Variability of Country Elevator Bid Prices*.

Donald J. Harmatuck, *Back Haul Pricing: Mathematical Programming and Game Theory Approaches to Allocating Joint Costs*.

Jeffrey L. Jordan, Dieudonne Mann, S. E. Pressia, and C. Thai, *Managing the Transportation of Perishable Commodities: Temperature Control and Stacking Patterns*.

1984 K. Eric Wolfe, *An Examination of Risk Costs Associated with the Movement of Hazardous Materials*.

1983 Denver D. Tolliver, *Economics of Density in Railroad Cost-Finding: Applications to Rail Form A*.

1982 Jeffrey Beaulieu, Robert J. Hauser, and C. Phillip Baumel, *Inland Waterway User Taxes: Their Impacts on Corn, Wheat and Soybean Flows and Transport Costs*.

Journal of the Transportation Research Forum
Guidelines for Manuscript Submission

1. Submit manuscripts by e-mail or hardcopy to either General Editor at:

Michael W. Babcock
Co-General Editor, JTRF
Department of Economics
Kansas State University
Manhattan, KS 66506 U.S.A.
Phone: (785) 532-4571
Fax: (785) 532-6919
Email: mwb@ksu.edu

James Nolan
Co-General Editor, JTRF
Dept. of Bioresource Policy, Business and Economics
University of Saskatchewan
Saskatoon, SK S7N 5A8 CANADA
Phone: (306) 966-8412
Email: james.nolan@usask.ca

2. E-mail submissions must be in MS WORD.

3. Final manuscript and abstract (hard or e-mail copy) must be received as soon as possible.

4. The text of manuscripts is to be double-spaced. Use one side of each page only. Articles are limited to a maximum length of 30 pages; industry issue papers and comments are limited to a maximum of 15 pages.

5. The manuscript should have a title page which includes the names, affiliations, address (mailing and e-mail) and phone numbers of all authors. Brief biographical sketches for all authors should be included with the manuscript.

6. The abstract should briefly describe the contents, procedures and results of the manuscript, not its motivation, and should not exceed 100 words.

7. Endnotes are to be used rather than footnotes, used sparingly and placed at the end of the manuscript. Do **NOT** use the endnote feature of the word processing software.

8. *The Chicago Manual of Style* is to be used for endnotes and references. At the end of the manuscript, complete references are listed alphabetically (not by number) by author surname, government agency, or association name. Use the following examples.

   Book:

   Jones, Robert T. *Improving Airline Transportation*. General Publishing Company, Washington, D.C., 2002.

   Chapter in a Book:

   Bresnahan, T.F. "Empirical Studies of Industries with Market Power." R. Schmalensee and R. Williq eds. *Handbook of Industrial Organization*. Amsterdam: North Holland (1989): 1011-1057.

   Journal Article:

   Kane, Louis R. "Grain Transport Rate Projections." *Transportation Journal* 2 (1999): 20-40.

   Journal Article with Multiple Authors:

   Chow, G., R. Gritta, and E. Leung. "A Multiple Discriminant Analysis Approach to Gauging Air Carrier Bankruptcy Propensities: The AIRSCORE Model." *Journal of the Transportation Research Forum* 31 (2), (1991): 371-377.

Ph.D Dissertation:

Jessup, E.L. "Transportation Optimization Marketing for Commodity Flow, Private Shipper Costs, and Highway Infrastructure, Impact Analysis." Dissertation (Ph.D). Washington State University, 1998.

Government Document:

U.S. Senate. Committee on Foreign Relations, *Investigations of Mexican Affairs*. 2 vols. 66th Cong., 2nd session, 1919-20.

9. Tables, figures, graphs, and charts should be titled and numbered by an Arabic numeral (e.g., Figure 2). All figures and charts should be submitted as **separate** files. Any graphics or photos must be 300 dpi and submitted as a separate .tif or .eps file.

10. Headings should adhere to the following style. Place the abstract below the title of the manuscript.

    • First level headings should be all caps, left justified.
    • Second level headings should be initial caps, left justified.
    • Third level headings should be initial caps on the same line as the first paragraph which it heads.
    • Do not number the headings.

11. Submit your final copy in "MS WORD" only.

12. For proper preparation of all charts, figures, maps and photos call Bev Trittin, North Dakota State University, at (701) 231-7137 or bev.trittin@ndsu.edu prior to submitting the final version of your paper. The journal is printed in black and white, therefore, all graphics must be submitted in black and white, or grayscale.

    TIPS:

    - Photographs to be submitted as individual files at 250 dpi or higher resolution (.jpg or .tif format).
    - Images taken from the web are 72 dpi and are not acceptable for print. Secure high resolution image when possible. Obtain permission for use of images taken from web.
    - Do not embed graphics in Word – submit as individual files (.jpg or .tif format).
    - If charts and figures are created in MS Excel, submit Excel file to Bev Trittin.
    - Improper graphics or images will be returned to author for correct formatting.

Book Review Information

Books for review should be mailed to:

Dr. Jack Ventura
Book Review Editor
1025 Chiswell Lane
Silver Spring, MD 20901
Phone: (301) 593-1872
Email: jack.ventura@verizon.net

JTRF Information

The Journal of the Transportation Research Forum is distributed to members of the Transportation Research Forum.

ISSN 1046-1469

The Transportation Research Forum gratefully acknowledges the contributions of sustaining and supporting members.

2015 Supporting Members

Michael Babcock, Kansas State University
Paul Gessner, Gessner Transportation Consulting, LLC
Jack Ventura
Jack Wells, U.S. DOT, retired