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**On the cover:** Tat Fu and co-authors discuss the process of adopting sustainable transportation by students, faculty and staff at two New England universities in "Exploring Sustainable Transportation Attitudes and Stages of Change Using Survey and Geospatial Data in New England Campus Commuters."

# A Message from the JTRF Co-General Editors

The Summer 2016 issue contains the usual wide variety of contemporary transportation topics that is the distinguishing characteristic of JTRF. Topics in this issue include the following:

- U.S. Air carrier financial condition
- Natural gas vehicles for the U.S. and Texas
- Safety impacts of converting two-way left-turn lanes to raised medians
- Random utility-based multiregional input-output model
- Exploring sustainable transportation attitudes
- Impacts of highway investment under the American Recovery and Reinvestment Act
- Classification system for public transportation.

In "Have the U.S. Air Carriers Finally Turned the Corner? A Financial Condition Assessment," Richard Gritta and Brian Adams analyze the recent performance of major airlines. The authors use a statistical model designed to predict the likelihood of financial stress for airlines. The authors update past research in the airline industry to demonstrate the precarious nature of profitability.

The authors briefly discuss the major reasons for the improvement of the industry's profitability. The authors concluded that the current financial condition has improved significantly due to increased concentration, market domination by some carriers, very low fuel costs, and record low interest rates.

Chen Xu and Liang-Chieh Cheng study adoption behavior for natural gas vehicles (NGVs) in "Adoption of Natural Gas Vehicles-Estimates for the U.S. and the state of Texas." The authors analyze NGV adoption behavior in both U.S. and Texas markets to estimate the dynamics of NGV diffusion. The authors employ Bass diffusion models to measure NGV adoption.

The authors found NGV markets appeared to have become saturated around 2010. This finding, they note, contrasts with anecdotal evidence about ongoing NGV adoption. They also found that NGV adoption through the imitation effect appears to be significant for the U.S. NGV market.

Priyanka Alluri, Albert Gan, and Kirelos Haleem conduct a detailed study of the safety impacts of conversion from two-way left-turn lanes (TWLTL) to raised medians on state roads in Florida, in "Safety Impacts of Converting Two-Way Left-Turn Lanes to Raised Medians and Associated Design Concerns." The authors investigated several potential safety concerns including crashes at median openings, vehicles hitting the median curb, and median crossovers crashes. The authors analyzed 17.51 miles of urban arterial sections in Florida that were converted from TWLTL to raised medians. They also reviewed police reports of all crashes before and after median conversion.

The authors found that the total crash rate decreased by 28.5% after the study locations were converted from TWLTLs to raised medians. They also found the reductions in left-turn and right-turn crashes were statistically significant, while the changes in other crash types were not significant. Overall, they concluded that raised medians are not an additional hazard compared to TWLTLs.

In "Local Sensitivity Analysis of Forecast Uncertainty in a Random-Utility-Based Multiregional Input-Output Model," Guangmin Wang and Kara Kockelman employ a Random-Utility Based Model (RUBMRIO) for trade and travel choices to appreciate the nature of commodity flow patterns across 3,109 U.S. contiguous counties and 12 industry sectors for rail and truck operations. The authors demonstrate the model's sensitivity to various inputs using the method of local sensitivity analysis with interactions (LSAI). The authors state that LSAI provides a valuable set of relationships to enable policy makers, planners, and carriers to quickly predict trade flows by producers' location

choices and production levels.

The model simulates both individual effects as well as interaction effects of model inputs on outputs by providing sensitivity indices of model outputs to variation of inputs under two scenarios. Scenario 1—simultaneously increasing all export demands (ED), transport costs (TC), and travel times (TT) between counties by 20%. Scenario 2—simultaneously decreasing all ED, TC, and TT by 20%.

The authors found that export demands (ED) are more important for accurately anticipating and quantifying trade flows than are TC and TT.

Tat Fu, Norbert Mundorf, Coleen Redding, Leslie Brick, Andrea Paiva, and James Prochaska present findings of a two-campus project designed to assess alternative sustainable transportation in "Exploring Sustainable Transportation Attitudes and Stages of Change Using Survey and Geospatial Data in New England Campus Communities." One of the objectives is to test the application of the Transtheoretical Model of Change (TTM) to transportation behaviors.

The authors found that commuting distances, transit connectivity, and status (student or faculty) affected commute modes and stages of readiness to use AT (alternative/ sustainable transportation). The authors reported that the survey data for AT replicated TTM relationship predictions between constructs and stages of change.

In "Impacts of Highway Infrastructure Investment Under the American Recovery and Reinvestment Act," Seong-Hoon Cho, Daegoon Lee, Dayton Lambert, and Roland K. Roberts evaluated the impact on highway demand of highway disbursement under the American Recovery and Reinvestment Act (ARRA). They measured the impact on highway demand by vehicle miles traveled and estimated a demand equation employing a spatial Durbin model for the 48 adjacent states. Estimates from the equation were used to test the hypothesis that highway disbursements caused different upward shifts in the highway demand curves of states.

The authors estimated $8.2 billion in total net benefits as a result of $27.2 billion in ARRA highway disbursements, fielding an average net benefit of $0.30 per dollar spent.

In "A New Model Classification System for Public Transportation," Arthur Guzzetti and John Neff take an inventory of all types of bus and rail mode classifications, discuss the issues associated with changing classifications, and introduce a revised classification of transit modes. The authors discuss the problems of the classifications employed by the American Public Transit Association (APTA). The Federal Transit Administration (FTA), and census bureau.

The authors point out that in 2011, the NTD subdivided their light rail category into three modes, commuter rail into two modes, and bus into three modes. In each case the former names, light rail, commuter rail, and bus, were used to identify one or two of the new subsets of the old modes. This may lead to errors in historical analysis. The authors say a better system uses new names to include all the previous modes to report data that are inclusive of the entire modal sets of transit systems. They note that this allows continuity of reporting data for the same groups of transit agencies for historical comparisons.

Michael W. Babcock
Co-General Editor-JTRF

James Nolan
Co-General Editor-JTRF

# Have the Major U.S. Air Carriers Finally Turned the Corner? A Financial Condition Assessment

**by Richard D. Gritta and Brian Adams**

*Rare prior to the deregulation of the airline industry, air carrier bankruptcies became rather endemic in the period 1982-2005. Since 1982, over 175 airlines have filed under the bankruptcy codes. This number includes eight of the carriers that were formerly referred to as "trunk carriers," now known as "Majors." Major carriers are defined as those with annual revenues exceeding $1.0 billion. The purpose of this paper is to analyze the recent performance of these carriers using a statistical model specifically designed to predict the likelihood of financial stress for airlines. The paper will also update past research in this important industry to demonstrate the very precarious nature of profitability. The major reasons for the improvement of the industry's profitability will be briefly discussed. The analysis will show that the current financial condition of the industry has improved significantly due to increased concentration and the market domination of some carriers, very low fuel costs facing the carriers, and the record low interest rates resulting from the Federal Reserve's easy monetary policy. the industry may still be fragile or vulnerable to changes in these input factors.*

## INTRODUCTION

The past several decades have been an extremely turbulent era for the U.S. airline industry. The events of 9/11, the steep increase in the price of fuel, and the great recession starting in 2008 all interacted to heighten the financial stress facing all airlines. With the recent additions in the mid-2000s of ATA, Aloha, Champion, Skyline, Pacific Western Air, Legend Air and others, the number of bankruptcy filings had risen to over 175 by 2016. All have filed since the deregulation of the airline industry in 1978. The vast majority of the total has been the smaller airlines categorized by the Department of Transportation (DOT) as large and medium regional air carriers. The major carriers, however, have suffered significantly. DOT classifies carriers by groups based on total dollar operating revenues. Major carriers have revenues of $1.0 billion or larger. The first filing was by the now defunct Braniff in 1982. The filings of major carriers (Braniff, Continental, Delta, Eastern, Northwest, PanAm, TWA, UAL, and USAir) have garnered the most attention for obvious reasons. Iconic carriers such as Braniff, Eastern, and PanAm have disappeared forever and the others have merged in order to survive. The purpose of this paper is to assess the current financial condition facing the major U.S. carriers as the U.S. economy continues to gain traction in 2016, outline briefly a few of the causes for what is found, and also to provide an overview of the risky nature of this industry.

## LITERATURE REVIEW AND METHODOLOGY

Applied financial ratio analysis has been around ever since there were income statements and balance sheets to assess. The quest, however, has been to combine these ratios into a score that could be useful in assessing the financial health of a firm over time. Beaver was the first (1966) to suggest that ratios analysis could have some predictive ability and utilized a univariate model using cash flow as the predictor. Altman (1968) then sought to advance the technique by developing the first generic bankruptcy scoring model using multiple ratios. Known as the Z Score, the model combined various balance sheet and income statement ratios using a regression technique known as Multiple Discriminant Analysis or MDA. The model was derived from data from a cross section of

different industries and has proven to be widely used (Altman 2006). Gritta (1982) used the model to predict the failure of Braniff and Continental before the events occurred. Altman et al. (1977) also sought to improve on Z Score with his ZETA® Model. Other techniques have been explored over the past several decades. Some researchers have used approaches such as Neural Networks (Zhang et al. 1999; Coats and Fant 1993), Genetic Algorithms (Carvalho and Freitus 2004; Varetto 1998), and Fuzzy Logic (Silva et al. 2005) in attempts to improve forecasting accuracy.

Models designed for specific industries, however, can be more powerful or accurate than generic models. Altman and Gritta (1984), for example, used the generic Altman ZETA® Model in assessing the U.S. air carriers,[1] but it was felt that models built on industry specific data might yield superior results. In fact, several researchers have used airline data to develop industry-specific models. One such model was called AIRSCORE (Chow et al. 1991). In addition, Gudmundsson (2002) employed a model which incorporated airline management variables that the author thought could further improve forecasting accuracy, and Silva et al. (2005) employed Fuzzy Logic to forecast air carrier stress. Finally, Pilarski and Dinh (1999) designed a model, called P-Score, specifically for air transportation. P-Score has the advantage that its inputs are readily available from data sources such as gurufocus.com and other sites. The P-Score model is a logit model that generates the probability of failure.[2] P-Score is calculated as follows:

(1) $W = -1.98X_1 - 4.95X_2 - 1.96X_3 - 0.14X_4 - 2.38X_5$

Where:

$X_1$ = operating revenues/total assets (REV/TA= a turnover ratio)
$X_2$ = retained earnings/total assets (RE/TA=a past profitability ratio)
$X_3$ = equity/total debt obligations (EQUITY/DEBT=a leverage measure)
$X_4$ = liquid assets/current maturities of total debt obligations (CA/CL= a liquidity ratio)
$X_5$ = earnings before interest and taxes/operating revenues (EBIT/REV=profitability)

(2) The number P is determined by: $P = 1/[1+e^{-w}]$

Financial analysts normally compute ratios which measure four aspects of financial health. Those measures are liquidity, leverage (use of debt finance), profitability, and turnover (efficiency). Several of the input ratios ($X_1$, $X_2$, and $X_3$) are ratios from the famous Altman Z Score model. Rather than producing a score that must be compared to a scale, as is the case with the previous models, this model produces the probability of bankruptcy. P is that probability. The higher the P value, the greater is the carrier's financial stress and the more likely it is to fail and vice-versa.

The majors assessed in this study are Alaska, American, Continental, Delta, JetBlue, SkyWest, Spirit, Southwest, United, and USAir. There have been a number of mergers that have affected the industry and thus this analysis. Northwest was merged into Delta, Continental into United, and TWA into American and recently USAir and American combined. All of these merged carriers have filed under the bankruptcy codes, in some cases more than once. Only passenger carriers are included in this study. All cargo carriers, such as FedEx, UPS, and DHL, are not.

Table 1 shows the application of P-Score to Southwest Airlines. The individual ratios are calculated from the carrier's income statements and balance sheets for the years 2003-2013. The source of the raw data was gurufocus.com. Southwest has always been regarded as the most profitable and stable airline in the industry, the result of superior operating strategies[3] and its far more conservative financial strategies over time.[4] This analysis clearly shows that excellent performance resulting from those operating and financial strategies. As the P-Scores indicate, its risk of failure has been the lowest relative to the rest of the carriers and is at or near 0%.

**Table 1: Southwest Air P-Scores**

| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **REV** | 5,937 | 6,530 | 7,584 | 9,086 | 9,861 | 11,023 | 10,350 | 12,104 | 15,658 | 17,088 | 17,699 |
| **EBIT** | 483 | 554 | 820 | 934 | 791 | 449 | 262 | 988 | 693 | 623 | 1,278 |
| **TA** | 9,878 | 11,337 | 14,218 | 13,460 | 16,772 | 14,308 | 14,269 | 15,463 | 18,068 | 18,596 | 19,345 |
| **RE** | 3,883 | 4,089 | 4,557 | 4,307 | 4,788 | 4,919 | 4,983 | 5,399 | 5,395 | 5,768 | 6,431 |
| **EQ** | 5,052 | 5,524 | 6,675 | 6,449 | 6,941 | 4,953 | 5,466 | 6,237 | 6,877 | 6,992 | 7,336 |
| **DEBT** | 4,826 | 5,813 | 7,543 | 7,011 | 9,831 | 9,355 | 8,803 | 9,226 | 11,191 | 11,604 | 12,009 |
| **CA** | 2,313 | 2,172 | 3,620 | 2,601 | 4,443 | 2,893 | 3,358 | 4,279 | 4,345 | 4,227 | 4,456 |
| **CL** | 1,723 | 2,142 | 3,848 | 2,887 | 4,838 | 2,806 | 2,676 | 3,305 | 4,533 | 4,650 | 5,676 |
| **X1** | 0.601 | 0.576 | 0.533 | 0.675 | 0.588 | 0.770 | 0.725 | 0.783 | 0.867 | 0.919 | 0.915 |
| **X2** | 0.393 | 0.361 | 0.321 | 0.320 | 0.285 | 0.344 | 0.349 | 0.349 | 0.299 | 0.310 | 0.332 |
| **X3** | 1.047 | 0.950 | 0.885 | 0.920 | 0.706 | 0.529 | 0.621 | 0.676 | 0.615 | 0.603 | 0.611 |
| **X4** | 1.342 | 1.014 | 0.941 | 0.901 | 0.918 | 1.031 | 1.255 | 1.295 | 0.959 | 0.909 | 0.785 |
| **X5** | 0.081 | 0.085 | 0.108 | 0.103 | 0.080 | 0.041 | 0.025 | 0.082 | 0.044 | 0.036 | 0.072 |
| **W** | -5.569 | -5.132 | -4.766 | -5.094 | -4.281 | -4.506 | -4.618 | -4.979 | -4.638 | -4.750 | -4.936 |
| P | 0.004 | 0.006 | 0.008 | 0.006 | 0.014 | 0.011 | 0.010 | 0.007 | 0.010 | 0.009 | 0.007 |

Source: Ratios and P values were calculated from raw data from gurufocus.com

Table 2 applies the model to the other major carriers for the years 2003-2013.

**Table 2: P-Scores 2003-2013**

| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **American** | 0.270 | 0.264 | 0.279 | 0.212 | 0.156 | 0.305 | 0.444 | 0.391 | 0.527 | 0.568 | 0.480 |
| **Delta** | 0.255 | 0.618 | 0.777 | 0.929 | 0.087 | 0.661 | 0.438 | 0.333 | 0.310 | 0.279 | 0.070 |
| **United** | 0.674 | 0.711 | 0.999 | 0.135 | 0.107 | 0.479 | 0.504 | 0.316 | 0.161 | 0.205 | 0.150 |
| **USAir** | 0.175 | 0.255 | 0.266 | 0.037 | 0.028 | 0.202 | 0.241 | 0.115 | 0.102 | 0.064 | merged |
| **Southwest** | 0.006 | 0.008 | 0.006 | 0.014 | 0.011 | 0.010 | 0.007 | 0.010 | 0.009 | 0.009 | 0.007 |
| **Alaska** | 0.069 | 0.067 | 0.066 | 0.074 | 0.059 | 0.114 | 0.080 | 0.044 | 0.033 | 0.022 | 0.009 |
| **JetBlue** | 0.063 | 0.093 | 0.136 | 0.133 | 0.135 | 0.130 | 0.112 | 0.088 | 0.079 | 0.064 | 0.050 |
| **SkyWest** | 0.006 | 0.005 | 0.039 | 0.016 | 0.013 | 0.011 | 0.020 | 0.019 | 0.012 | 0.012 | 0.012 |
| **Spirit** | na | na | na | na | na | 0.449 | 0.203 | 0.103 | 0.001 | 0.001 | 0.000 |

Source: Calculated from raw data on gurufocus.com

Several important facts are evident from Table 2. Absent Southwest, Alaska, and SkyWest (the latter just recently defined as a major), the largest carriers have had a very turbulent history over the past decade and a half. The result has been the mergers mentioned above. The failed carriers, Continental, Delta, Northwest, TWA, United, and USAir, consummated mergers in order to survive.[5] While the events of 9/11 and the real estate crash causing the Great Recession have been responsible for dramatic increases in the likelihood of failure, American, Delta, and United, the three largest carriers, were still facing some problems according to the P-Scores. What really stands out is the ability of carriers, like Southwest and SkyWest to prosper in spite of 9/11 and the Great Recession. It does appear that the model shows an improvement in the carriers' financial health over the time horizon spanning 2003-2013. Further improvement has continued into late 2015. Table 3 lists the P-Scores for the carriers for the past almost two years. The 2015 results are for the third quarter of this year.

**Table 3: P-Scores 2014-2015**

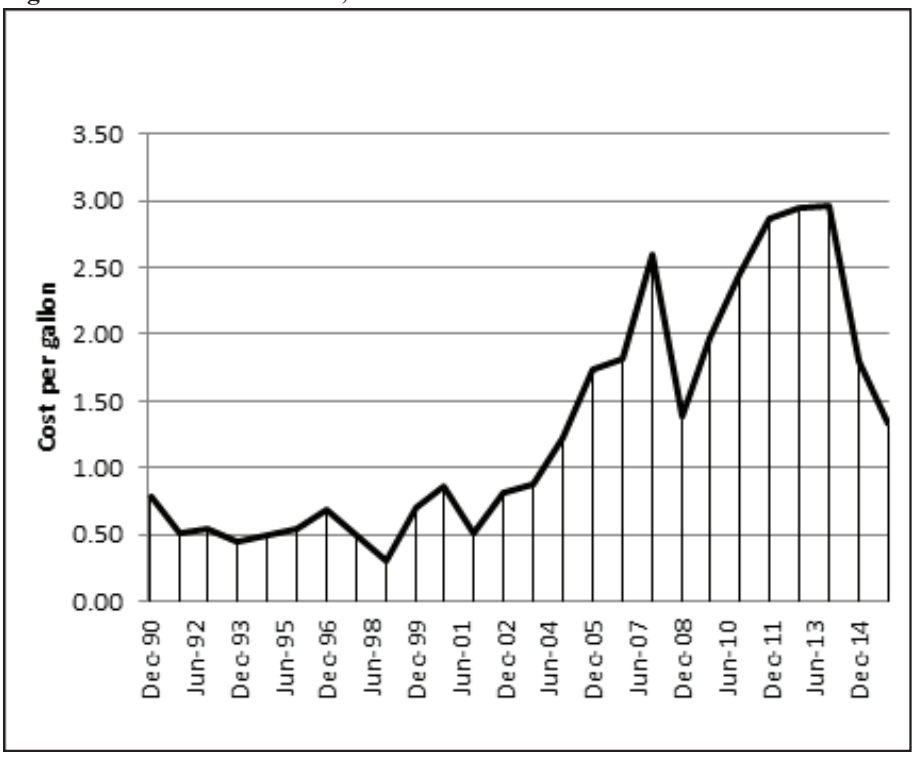
| | 2014 | 2015 |
|---|---|---|
| **American** | 0.195 | 0.134 |
| **Delta** | 0.000 | 0.000 |
| **United** | 0.143 | 0.092 |
| **Southwest** | 0.004 | 0.000 |
| **Alaska** | 0.008 | 0.004 |
| **JetBlue** | 0.033 | 0.010 |
| **SkyWest** | 0.004 | 0.002 |
| **Spirit** | 0.000 | 0.000 |

Source: Calculated from data in carrier reports

The financial conditions of American, Delta, and United have dramatically improved, especially over the last several years, and the trends appears to be very positive. The big question is the "why" and the "whether if" this trend can persist and thus break the boom-bust cycle that has been so predominant in the history of this industry.

There seem to four major reasons for the significant improvement in the carriers' financial condition. Two are more obvious. The first is that the economy has continued to grow, albeit somewhat slowly, out of the Great Recession. The second is the very low interest rates (due to Federal Reserve policies to assist the economic recovery) that have lowered the cost of capital to the carriers. The other two are not as obvious. The following figure shows the third key factor. Fuels costs have declined sharply due to the fall in oil prices to less than $35 a barrel in December 2014.

**Figure 1: Aviation Fuel Prices, December 1990−December 2015**



The fourth factor is the greatly increased concentration in the industry. The significance of the mergers of Delta/Northwest, United/Continental, and American/USAir cannot be understated.[6] The industry has been moving increasingly toward an oligopoly situation. This has allowed carriers to control air fares in many markets, impose extra charges on virtually everything from baggage to food to aisle seats, and the level of services passengers must endure.

There are several widely accepted measures used to demonstrate the existence of an oligopoly. Two important standards are the four-firm and eight-firm concentration ratios. The concentration ratios show the percentage of domestic revenue passenger miles for each carrier. Table 4 shows the changes over time of the two measures. The four-firm and eight-firm concentration ratios have been used in many court antitrust cases to judge the presence of an oligopoly.[7]

**Table 4: Concentration Ratios Domestic Revenue Passenger Miles**

| Year | 4 Firm | 8 Firm |
|---|---|---|
| **1975** | 52% | 81% |
| **1980** | 50% | 80% |
| **1985** | 50% | 77% |
| **1990** | 52% | 76% |
| **1995** | 58% | 77% |
| **2000** | 56% | 85% |
| **2005** | 59% | 86% |
| **2010** | 61% | 88% |
| **2015** | 70% | 84% |

Source: Air Carrier Traffic Statistics – various issues

Clearly there is an oligopoly developing in the domestic market, and passengers have felt the effects noted just above.

## CONCLUSION

The purpose of this paper was to assess the current financial condition of the airline industry. The scores have proven to be good at indicating the impending changes in the financial condition of carriers over time. The P-Score model clearly does a good job of measuring financial strength, and the study shows the significant ups and downs of air carriers over the past decade.

What is the answer to the question posed in the title of this paper? Based on the P-Score analysis, it appears that all of the major carriers have substantially improved their financial condition over the past several years. All have benefited from several factors which have dramatically increased profits. These include the huge decline in the price of a barrel of oil, the record low interest rates, the mergers that have increased the concentration of the four largest carriers, and the gradual improvement in the U.S. economy.

The failure rate of air carriers over the past 30 years has simply been abysmal[8], and the P-Scores clearly demonstrate the fact that the risk could once again increase should if oil prices spike upwards, interest rates return to normal levels, or the economy falters. Things could also change should the USDOT and the Dept. of Justice choose to enforce anti-trust laws. In any case, the model is a tool useful to a wide audience involved with the air transport industry, including stockholders, bondholders, banks, lessors and other creditors, and governmental agencies that need to be able to gauge financial stress and the likelihood of future problems. Finally, the model can be of aid to one other group not mentioned above. That group is airline management. The models show the variables that are critical to successful financial performance. Management can thus center on actions that will

improve the variables key to reversing the low and negative trends in the ratios, at least in part due to managerial mistakes in the areas of financial leverage, liquidity, and profitability.

**Endnotes**

1. Other researchers have built industry specific models; Brocket et al. (1994) in the insurance industry and Altman (1973) specified models for industries such as the U.S. railroad industry and for over-the counter securities dealers.

2. The AIRSCORE and P-SCORE models were generated using only air carrier data, but since the former requires data not readily available to the average person, this paper centers on the latter. AIRSCORE was developed by one of the current authors (Chow, Gritta, and Leung 1991). The International Center for Air Transportation at MIT [ICAT] has used the AIRSCORE model to track airlines, and both the U.S. Department of Transportation and the FAA have utilized two of the authors' models in the past. Neural Nets and Genetic Algorithms have also been designed to assess the airline industry. For a summary of these approaches, see: (Gritta, Davalos, and Adrangi 2006).

3. Lower costs per ASM (available seat mile) resulted from its hedging of fuel costs, its use of one type of aircraft (the B737), which minimizes pilot training expenses, and the carrier's better than average relationship with its union employees (at least in the past). In addition, while Southwest does use a hub and spoke system, it operates its system less rigidly that some other carriers.

4. Several studies have outlined the nature of risk in this industry and detailed Southwest's minimal use of long-term debt finance and its effect on carrier stability. See, for example: (Gritta, Adrangi, and Adams 2006) and Gritta, Freed, and Chou (1998).

5. A history of both the P-Scores and the Z Scores dating back to 1990 can be found in Goodfriend et al. (2004).

6. The combination of American and USAir resulted when the latter bought the former out of bankruptcy in spite of the fact that the combined carrier bears the American name.

7. Others are the Gini Coefficient, Herfindal Index, and Lorenz Curve. For a prior example applied to the air carriers, see Adrangi and Gritta (1986).

8. It is hard to find a major industry in the U.S. economy, especially one so important in the U.S. economy, that has suffered as high a failure rate as have the air carriers. The following major carriers have filed one or more times: American, Braniff, Continental, Delta, Eastern, Northwest, TWA, United, and USAir. In addition, other carriers classed as majors, formerly known as "trunklines" in the period 1970-1980, have filed. This list includes Braniff, Eastern, TWA, and PanAm (although the latter was classed as an "International." These have all disappeared and TWA was merged into American.

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# Adoption of Natural Gas Vehicles – Estimates for the U.S. and the State of Texas

**by Chen (Sarah) Xu and Liang-Chieh (Victor) Cheng**

*Natural gas vehicles (NGV) have attracted more and more attention from policy makers since natural gas is a clean substitute for traditional fossil fuel that is also readily accessible. In some areas such as the state of Texas, vehicles that do not use traditional fossil fuel (e.g., NGVs) are exempt from paying fuel taxes. Government financial incentives have motivated substantial adoption of NGVs. This paper studies NGV adoption behavior in both U.S. and Texas markets to estimate the dynamics of NGV diffusion. This research employs well-known Bass diffusion models applied to NGV adoption, using data from both the U.S. and Texas. Among several interesting results, we find that NGV adoption through an imitation effect appears to be significant for the U.S. NGV market.*

## INTRODUCTION

Natural gas vehicle (NGV) technologies have gained a stronger presence in U.S. alternative vehicle markets. Within the past few years, counts of NGVs across the US have increased steadily, starting from 23,281 in 1992 to 121,650 in 2011 (Alternative Fuels Data Center 2014). In addition, multiple agencies predict that heavy-duty NGVs in the U.S. will have a penetration rate of 40% or higher by 2050 (National Energy Information Center 2010; National Petroleum Council 2012). For transit buses, a forecast of the US Department of Energy shows that natural gas fuels may garner upwards of 65% of total U.S. transit fuel usage by 2035 (National Energy Information Center 2010). Other studies report growing market penetration trends for NGVs in light-duty and medium-duty U.S. auto markets (National Petroleum Council 2012). Overall, a consensus is emerging that there will be continued growth in the use of NGVs across most U.S. transportation sectors.

In addition, the price spread between conventional and natural gas fuel will be a key economic driver for future NGV adoption in the United States. For decades, the price of natural gas has been about one half or even a third of conventional fuels, namely gasoline and diesel (Alternative Fuels Data Center 2014). Even though greater market penetration of NGVs could drive up natural gas prices, abundant supplies from U.S. domestic shale natural gas production should be able to meet domestic demand for natural gas fuels (U.S. Energy Information Administration 2015). In the meantime, increasing prices for conventional fuels contribute to a continuing price spread between conventional and natural gas fuel (Alternative Fuels Data Center 2014; National Petroleum Council 2012). The potential for cost savings by using natural gas instead of conventional fuels remains a strong incentive for the public and U.S. urban transportation fleets to adopt NGVs.

Environmentally, NGV is also a cleaner fuel option, producing less air pollution and greenhouse gas emissions than conventional fuels. For example, natural gas produces far less $CO_2$ compared with gasoline and diesel. Natural gas also yields lower levels of $NO_x$ and sulfur, additional components of greenhouse gases. In highly populated areas, higher adoption rates for NGVs could lead to significant improvements in air quality and a reduction of air pollution, as well as reducing pollution-related diseases and associated social costs (Engerer and Horn 2010; Pasaoglu, Honselaar, and Thiel 2012).

Growth of NGVs could also help the U.S. energy sector reduce dependence on petroleum-based fuels. Transportation fuels generate more than half of energy use in the United States (National Energy Information Center 2010). Furthermore, using U.S. domestically produced fuels reduces the U.S. economy's dependence on major oil and gas producing countries. Natural gas as a fuel could also help mitigate the consequences of growing energy consumption by large oil and gas consuming

countries, such as China and India. Adopting NGVs also can diversify the use of technologies to power vehicles, such as natural gas, propane, electricity, as well as conventional fuels.

There has been a body of qualitative studies predicting an optimistic landscape for NGV adoption in the U.S. auto market. However, to the knowledge of the authors, the potential trajectory of NGV adoption and diffusion has not yet been quantitatively examined. For example, little is known about NGV growth patterns over a longer time horizon. Even those states leading NGV adoption display different growth rates in terms of specific annual market growth. In order to better understand the use and diffusion of NGVs in the U.S. moving forward, we offer that potential NGV technology diffusion within the U.S. as well as key state level markets needs to be quantitatively examined.

It is clear that the diffusion of NGV technologies is strongly conditioned by natural gas prices and the coverage of natural gas refueling infrastructure. Accordingly, a realistic NGV forecast model requires simultaneous assessments of changes in both prices and infrastructure. In fact, a few studies in the extant literature on alternative vehicle technologies examine in detail price and infrastructure effects with respect to a demand forecast model (Park, Kim, and Lee 2011).

This paper will estimate models of the diffusion of NGV technology. These models will also help us to better understand the nature of NGV penetration across both the U.S. and Texas automobile markets. By conducting this analysis, it is our hope to shed some light on the nature of current NGV market growth as well as the future of NGV adoption both in the U.S. and Texas.

## LITERATURE REVIEW

There has been a previous body of literature that studies forecasts for adoptions of various vehicle technologies. Researchers have applied a variety of statistical models to assess or forecast demands for vehicles with conventional and alternative fuel technologies. One stream of vehicle technology adoption research applies time-series or causal relationship modeling techniques.

As an example of the above, Garcia-Ferrer et al. (1997) applied an autoregressive integrated moving average (ARIMA) model to study the evolution of the Spanish automobile industry. Shahabuddin (2009) developed several regression models and used historical data (1959-2006) to forecast US automobile sales. On a much broader scale, Dargay and Gately (1999) applied causation regression modeling techniques to predict worldwide vehicle ownership. Regression modeling research requires inputs of historical socioeconomic data that are often collected from public sources. It should be noted that time-series or causation models have typically only been used to model technology adoption of conventional fuels, i.e., gasoline and diesel. Trends for alternative fuel vehicle technologies (AFVTs) cannot be easily derived from these studies because the shares of AFVTs are small. In new AFVT markets, technology adoption data may not exist or simply be too limited to perform reliable statistical analyses.

Other widely used modeling techniques in this area are known as consumer choice models (Menon and Biswajit 2012). Consumer choice studies use surveys to gather data on respondents' personal characteristics and vehicle technology attributes. In turn, discrete choice models are applied to analyze the survey data and determine the effects of personal characteristics and technology attributes on the market share of each vehicle technology (Lee and Cho 2009). Consumer choice models rely on data from surveys, which usually are expensive to conduct. In addition, surveys are most often cross-sectional, and broader market share forecasts need extrapolations that can lead to imprecise predictions (Potoglou and Kanaroglou 2008).

In the case of sparse data for adoption of new vehicle technologies, multiple diffusion forecast models have been developed in the AFVT adoption literature. Researchers have applied Gompertz, Logistic, Bass, and Generalized Bass (GBass) diffusion models to forecast diffusion rates of AFVTs, e.g., electric vehicles (EVs) and NGVs. All four specifications demonstrate the well-known S-shaped diffusion curve associated with adoption of new technologies, and all have a fixed saturation level

(McManus and Senter 2009). But Gompertz, Logistic, and Bass specifications require only one variable and produce unconditional forecasts (Wilson and Keating 2009), while in contrast, GBass functions allow more explanatory variables into the model, which can help better determine the shape of the S-curve. The following sections highlight those studies applying Bass and GBass models to study technology as well as AFVT diffusions (Park, Kim, and Lee 2011).

**The Bass Technology Diffusion Model**

Several quantitative studies have applied the classic Bass model (Bass 1969) to estimate market penetration of new technology. The Bass model explains how consumers move from one potential social group to an adopter social group. The salient feature of the Bass diffusion model is the S-shaped market growth for new technologies. Growth rates within the S-shaped diffusion curve are determined by three parameters: $p$, the rate of initial adoption by users independent of marketing efforts for the new technology; $q$, the imitation rate of technology users, who follow word-of-mouth information in order to decide upon adoption; and $M$, the maximum market potential of the new technology.

Chang and Wang (2011) used the Bass diffusion model to forecast growth patterns for Twitter adoption and hashtag diffusion in Taiwan. Heinz et al. (2013) applied the Bass model to study stationary fuel cell diffusion. Their Bass estimates showed that a fuel cell market will reach half of the maximum market size within five years, and after eight years the market will be close to projected full market size. Finally, Becker et al. (2009) utilized the Bass diffusion model to predict the U.S. EV penetrations to 2030. The study predicted that the EV penetration can reach 24% of the U.S. light-duty fleet. The researchers also estimated the reduction of emissions resulting from EV growth.

**The Generalized Bass Technology Diffusion Model**

Bass et al. (1994) further developed what they called the Generalized Bass (GBass) model of technology diffusion. This specification included not only internal, but also external marketing variables into diffusion estimates. Essentially, Bass et al. (1994) included a mapping function consisting of a mix of marketing variables into the original Bass model. Unlike the basic version, the GBass model incorporates additional variables intended to capture the effects of marketing actions. In turn, these variables may change the shape of the diffusion curve as well as the ultimate market potential estimate (McManus and Senter 2009).

Estimating both Bass and GBass models will generate richer output and provide better insight into the marketing characteristics of the market under study. Examples using the GBass model include Park et al. (2011), who estimated a GBass diffusion model to understand market penetration for Hydrogen Fuel Cell Vehicles (HFCVs) in Korea (Park, Kim, and Lee 2011). In the U.S., researchers have forecast the diffusion processes of Plug-In Hybrid Electric Vehicles (PHEVs) (McManus and Senter 2009), while the same researchers also utilized a GBass approach to estimate PHEV penetration (McManus and Senter 2009).

There are a number of interesting features of these latter studies. First, the critical $p$, $q$, and $M$ parameter values were similar across both Bass and GBass estimates; in fact, the Bass and GBass curves behaved very similarly with the PHEV data. Finally, $p$ and $q$ were both significant in the Bass model; whereas in the GBass model, all parameters except $q$ were statistically insignificant. These insignificant parameters suggest a need to explore additional decision variables that may affect technology diffusion and the growth of alternative vehicle markets.

In summary, among the various technology diffusion estimation techniques, Bass and GBass models allow incorporation of consumer behavior into the model specifications. Moreover, the additional flexibility to include socioeconomic variables in the GBass model gives more

interpretational flexibility to the forecasts. By contrast, Gompertz and Logistic diffusion models do not have simple microeconomic interpretations and, hence, do not generate ready explanations for consumer adoption of AVFTs (Wilson and Keating 2009).

## MODEL DEVELOPMENT

### Bass Model for NGV Diffusion

Bass technology diffusion is driven by the concept that there exists some probability of new adoption of a technology in the marketplace. Specifically, the probability of new adopters for the focal technology (i.e., NGV) that have not already adopted is a linear function of existing adopters of this technology which have adopted it (Bass 1969). The analytic expression is:

(1) $P(t) = p + (q/M)A(t)$

$P(t)$ = the probability that an initial NGV purchase (in this case) will be made at $t$, given that no purchase has yet been made, is just a linear function of the number of previous buyers (Bass 1969);
$p$ = the coefficient of "innovation," meaning independent technology adoption without external influences;
$q$ = the coefficient of imitation, meaning adoption following independent or other adopters; or, alternatively, a measure of network influence;
$A(t)$ = the number of previous buyers, where $A(0) = 0$;
$M$ = the total initial purchase of the product over the period of interest (i.e., the life of the product).

Statistically, equation (1) is a hazard function that shows the limiting probability that a potential NGV user who has not adopted before time t does so at time t. While p represents the rate of initial adoption by users independent of marketing efforts for the new technology, q represents the imitation rate of technology users who follow information from social networks to make decisions about adoption. Intuitively, p and q are positive in that independent adopters and follower adopters must coexist in the (AFVT) marketplace. However, the coefficient of p is likely to be relatively small, meaning less risk-seeking behavior associated with AFVT adoption. The coefficient of q, in contrast, is expected to be larger than p, indicating more risk-averse behavior associated with AFVT adoption. Finally, we predict that M, the maximum market potential of the NGV technology, is going to be positive.

Under these assumptions, the likelihood of a purchase at time t given that no purchase has yet been made is (Bass 1969):

(2) $$\frac{f(t)}{1-F(t)} = P(t) = p + \left(\frac{q}{M}\right)A(t) = p + qF(t)$$

$f(t)$ = the likelihood of purchase at $t$

The cumulative possibility of purchase over period $t = [0, T]$ is;

(3) $$F(t) = \int_0^t f(t)\,dt, and\ F(0) = 0$$

So we can compute sales at time $t$, $S(t)$, as;

(4) $$S(t) = Mf(t) = (p + \frac{q}{M}\int_0^t S(t)dt)(M - \int_0^t S(t)dt)$$

In turn, the total number purchasing during the time interval [0, t] is

(5) $A(t) = \int_0^t S(t)dt = M\int_0^t f(t)dt = MF(t)$

So the ultimate solution to the Bass model is (Bass 1969):

(6) $F(t) = \frac{1-e^{-(p+q)t}}{1+(\frac{q}{p})e^{-(p+q)t}}$

Meaning that the total number purchasing during the time interval [0, t] is

(7) $A(t) = F(t)M = M\frac{1-e^{-(p+q)t}}{1+(\frac{q}{p})e^{-(p+q)t}}$

**Generalized Bass Model for NGV Diffusion (Bass et al. 1994)**

The updated GBass differential equation describing technology diffusion multiplies the original Bass differential equation by an additional expression, $x(t)$. As mentioned, $x(t)$ is an equation which contains marketing variables associated with the technology diffusion model. In the AFVT literature, a variety of marketing variables have been studied. In our context, sales of NGVs at time $t$, $S(t)$, is (Bass et al. 1994):

(8) $S(t) = (p + \frac{q}{M}A(t))(M - A(t))x(t)$

where

(9) $x(t) = 1 + \beta_1\frac{P\prime}{P} + \beta_2\frac{G\prime}{G}$

$\beta_1$ the effect of the price premium for natural gas fuels on NGV adoptions;

$\beta_2$ the effect of the number of natural gas refueling stations on NGV adoptions;

Intuitively, $\beta_1$ should be negative since higher prices for natural gas fuels are likely to lower NGV demand. $\beta_2$ is expected to be positive because greater availability of natural gas refueling infrastructure will motivate more NGV demand. Next, let us define the change in the natural gas fuel price premium by:

(10) $P(t) = \frac{price\ of\ conventional\ fuel - price\ of\ natual\ gas}{price\ of\ conventional\ fuel\ vehicle}$

and the change in the number of natural gas stations by:

(11) $G(t) = \frac{\textit{No. of NG refueling station at time } t - \textit{No. of NG refueling station at time } (t-1)}{\textit{No. of NG refueling station at time } t}$

So in this case, the solution to our version of GBass model is:

(12) $A(t) = M(\frac{1-e^{-(p+q)(t+\beta_1\ln(P(t))+\beta_2\ln(G(t)))}}{1+(q/p)e^{-(p+q)(t+\beta_1\ln(P(t))+\beta_2\ln(G(t)))}})$

**Statistical Estimation Methods for Bass and GBass Models.**

Several methods have been used to estimate key parameters in the Bass and GBass models. A basic non-linear regression of the equation specification is the most common approach for both the Bass and GBass model specification. With respect to model estimation, we specify here the observational data as a nonlinear combination of parameters and independent variables (Guseo and Dalla Valle 2005). The general objective function used for our non-linear regression is (Greene 2000):

(13) $\min \sum_1^N (y - f(x))^2$

$N$ = the total number of pairs of observations and independent variables in the dataset;
$y$ = the vector of observed dependent variables;
$x$ = the vector of independent variables;
$f(x)$ = the model function.

Methods to solve nonlinear regression problems can be tricky and vary from one software package to another. Keeping with prior studies, here we start by using STATA (Version 9) as our non-linear estimation package. The primary reason for doing this is that STATA is well established as an econometric and statistical software and in turn is relatively easy for a researcher to use (McManus and Senter 2009; Popp, Hascic, and Medhi 2011).

## DATA DESCRIPTION

### Data Sources

We collected national and state (Texas) data on NGVs as well as natural gas refueling stations. Several U.S. archival sources were utilized to gather these data. These include the Federal Highway Administration, the Bureau of Transportation Statistics, the U.S. Energy Information Administration (EIA), and the Alternative Fuels Data Center. We also note that the U.S. Department of Transportation (DOT), Department of Energy (DOE), and Energy Information Administration (EIA) publish national and state-specific data on NGVs and refueling stations.

### NGV Penetrations in U.S. National Auto Markets

Table 1 presents the U.S. Census Bureau summary counts of vehicles powered by alternative fuels during the period 2003-2009. The data source is the U.S. DOT (Federal Highway Administration 2014; U.S. Census Bureau 2015). The table shows estimated consumption of vehicle fuels by fuel type. Six primary categories of fuel are listed in the table. These are compressed natural gas (CNG), electric, ethanol 85% (E85), liquefied natural gas (LNG), and liquefied petroleum gas (LPG). Among these, two fuel types can be summarized as natural gas vehicles: CNG and LNG. The total number of CNG vehicles was 114,406 in 2003 and 114,270 in 2009. LNG vehicles increased from 2,640 to 3,176 over 2003 to 2009. In terms of vehicles in use, NGVs comprise a nontrivial market force among the set of alternative fueled vehicles in the U.S. Note that while the total number of NGVs in use has stayed above 117,000 over time, the NGV percentages decreased from 21.92% to 14.21% during 2003-2009.

Table 2 summarizes the data from the Energy Information Administration and shows the number and proportion NGVs compared to the total number of vehicles. The total number of NGVs increased from 117,046 to 121,254 during 2003-2011. Among NGVs, there are significantly more CNG vehicles than LNG vehicles. Finally, starting from 2003, we note that the percentage of NGVs

over all ground vehicles is less than 0.0006%. The percentage remained almost the same over this time, only showing slight fluctuation below a range of .01%.

**Table 1: Alternative Fueled Vehicle Counts, by Fuel Type**

| Type of Alternative Fuels | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 |
|---|---|---|---|---|---|---|---|
| Compressed Natural Gas (CNG) | 114,406 | 118,532 | 117,699 | 116,131 | 114,391 | 113,973 | 114,270 |
| Liquefied Natural Gas (LNG) | 2,640 | 2,717 | 2,748 | 2,798 | 2,781 | 3,101 | 3,176 |
| Total NGV | 117,046 | 121,249 | 120,447 | 118,929 | 117,172 | 117,074 | 117,446 |
| NGV Percentage | 21.92% | 21.44% | 20.34% | 18.74% | 16.84% | 15.09% | 14.21% |
| Electric | 47,485 | 49,536 | 51,398 | 53,526 | 55,730 | 56,901 | 57,185 |
| Ethanol, 85 percent (E85) | 179,090 | 211,800 | 246,363 | 297,099 | 364,384 | 450,327 | 504,297 |
| Hydrogen | 9 | 43 | 119 | 159 | 223 | 313 | 357 |
| Liquefied Petroleum Gas (LPG) | 190,369 | 182,864 | 173,795 | 164,846 | 158,254 | 151,049 | 147,030 |
| Other Fuels | 0 | 0 | 3 | 3 | 3 | 3 | 3 |
| **Total** | 533,999 | 565,492 | 592,125 | 634,562 | 695,766 | 775,667 | 826,318 |

Source: US Census Bureau (2015).

**Table 2: NGVs Number and Percentage in the U.S.**

| YEAR | CNG | LNG | NGV TOTAL | ALL VEHICLES | CNG (%) | LNG (%) | TOTAL (%) |
|---|---|---|---|---|---|---|---|
| 2003 | 114,406 | 2,640 | 117,046 | 231,000,000 | 0.000494 | .0000114 | 0.000506 |
| 2004 | 118,523 | 2,644 | 121,167 | 237,000,000 | 0.0005 | .0000111 | 0.000511 |
| 2005 | 117,511 | 2,687 | 120,198 | 241,000,000 | 0.000487 | .0000111 | 0.000498 |
| 2006 | 116,100 | 2,747 | 118,847 | 244,000,000 | 0.000475 | .0000113 | 0.000487 |
| 2007 | 114,359 | 2,727 | 117,086 | 247,000,000 | 0.000462 | .000011 | 0.000474 |
| 2008 | 113,940 | 3,028 | 116,968 | 248,000,000 | 0.000459 | .0000122 | 0.000471 |
| 2009 | 114,237 | 2,869 | 117,106 | 246,000,000 | 0.000464 | .0000116 | 0.000475 |
| 2010 | 115,817 | 3,030 | 118,847 | 242,000,000 | 0.000478 | .0000125 | 0.000491 |
| 2011 | 118,168 | 3,086 | 121,254 | 25,3000,000 | 0.000467 | .0000122 | 0.000479 |

Source: Energy Information Administration (2013).

## NGV Penetration in Texas Auto Markets

In order to estimate the penetration of NGVs in Texas' auto markets, we reviewed vehicle data from several federal datasets (Bureau of Transportation Statistics 2002, 2014; Federal Highway Administration 2014; U.S. Census Bureau 2015; U.S. Energy Information Administration 2013). The U.S. EIA provides data on state-specific alternative fuel vehicle counts. Table 3 shows Texas NGVs' and other alternative vehicles' historical levels and percentages. In 2003, the number of CNG vehicles in Texas was around 6,927, while LNG numbers were about 604 vehicles, so that total NGV numbers were about 7,531 vehicles. The EIA reports that after 2003, the total number of NGVs increased from 7,531 to 11,185 over nine years. We note that CNG vehicles are the main

contributor to increasing NGV penetration. The number of LNG vehicles actually fell over this time. In any case, the CNG vehicle sector still represents around 0.000553 % of all Texas vehicles, a relatively small ratio.

**Table 3: Texas NGV Number and Percentage**

| Year | CNG | LNG | NGV TOTAL | ALL VEHICLES | CNG (%) | LNG (%) | TOTAL (%) |
|---|---|---|---|---|---|---|---|
| 2003 | 6,927 | 604 | 7,531 | 14,888,780 | 0.000465 | .0000406 | 0.000506 |
| 2004 | 10,160 | 558 | 10,718 | 16,906,714 | 0.000601 | .000033 | 0.000634 |
| 2005 | 11,376 | 501 | 11,877 | 17,469,547 | 0.000651 | .0000287 | 0.00068 |
| 2006 | 11,026 | 550 | 11,576 | 17,538,388 | 0.000629 | .0000314 | 0.00066 |
| 2007 | 10,827 | 411 | 11,238 | 18,072,148 | 0.000599 | .0000227 | 0.000622 |
| 2008 | 11,032 | 422 | 11,454 | 18,207,948 | 0.000606 | .0000232 | 0.000629 |
| 2009 | 10,125 | 315 | 10,440 | 18,208,170 | 0.000556 | .0000173 | 0.000573 |
| 2010 | 11,275 | 319 | 11,594 | 17,193,559 | 0.000656 | .0000186 | 0.000674 |
| 2011 | 10,845 | 340 | 11,185 | 19,617,055 | 0.000553 | .0000173 | 0.00057 |

Source: Energy Information Administration (2013).

In addition, we collected data from the U.S. EIA to calculate the percentage of different types of NGVs in the Texas vehicle market (see Table 4). Here, pickup and van categories comprise the majority of total NGVs. Pickups have approached half of total vehicle numbers, while in contrast, the SUV category occupies the smallest market share of NGVs in Texas.

**Table 4: Different NGV Types in Texas**

| Year | Van | Pickup | Truck | Bus | SUV | Other | Total |
|---|---|---|---|---|---|---|---|
| 2003 | 580 | 3,240 | 1,432 | 476 | 165 | 1,034 | 6,927 |
| 2004 | 1,132 | 4,210 | 1,535 | 780 | 294 | 2,209 | 10,160 |
| 2005 | 999 | 4,523 | 1,869 | 662 | 219 | 3,104 | 11,376 |
| 2006 | 1,778 | 5,350 | 985 | 680 | 238 | 1,995 | 11,026 |
| 2007 | 1,739 | 4,997 | 688 | 769 | 241 | 2,393 | 10,827 |
| 2008 | 1,650 | 4,557 | 524 | 1,133 | 255 | 2,913 | 11,032 |
| 2009 | 1,608 | 4,458 | 381 | 1,345 | N/A | 2,333 | 10,125 |
| 2010 | 1,624 | 4,877 | 551 | 1,452 | 357 | 2,414 | 11,275 |
| 2011 | 2,153 | 4,538 | 521 | 1,084 | 7 | 2,542 | 10,845 |

Source: Energy Information Administration (2013)

In terms of U.S. natural gas refueling infrastructure, the number of CNG stations reached the 100 station threshold in 1996. Since then, the number of CNG stations has risen. In contrast, U.S. LNG stations display a slower growth rate and only reached 100 stations nationwide in 2014. Public stations and private stations are distinct service groups for NGV refueling infrastructure. Public stations are similar to the widespread gasoline and diesel refueling stations, and the services are open for public NGV adopters. In contrast, private stations are reserved for NGV fleets owned by private or public organizations, such as carriers, businesses, and governments (National Petroleum Council 2012).

By the end of 2013, there were 1,305 CNG stations (657 public stations and 648 private stations) and 88 LNG stations (47 public stations and 41 private stations). By the summer of 2014, there were

1,399 CNG refueling stations (732 public stations and 667 private stations) and 100 LNG refueling stations (58 public stations and 42 private stations) across the United States. Figure 1 illustrates the growth of CNG stations and the relative distribution between public and private refueling stations over time. Figure 2 shows and contrasts growth rates of both U.S. CNG and LNG stations.

**Figure 1: US CNG Station Growth and Distribution of Public vs. Private Stations**

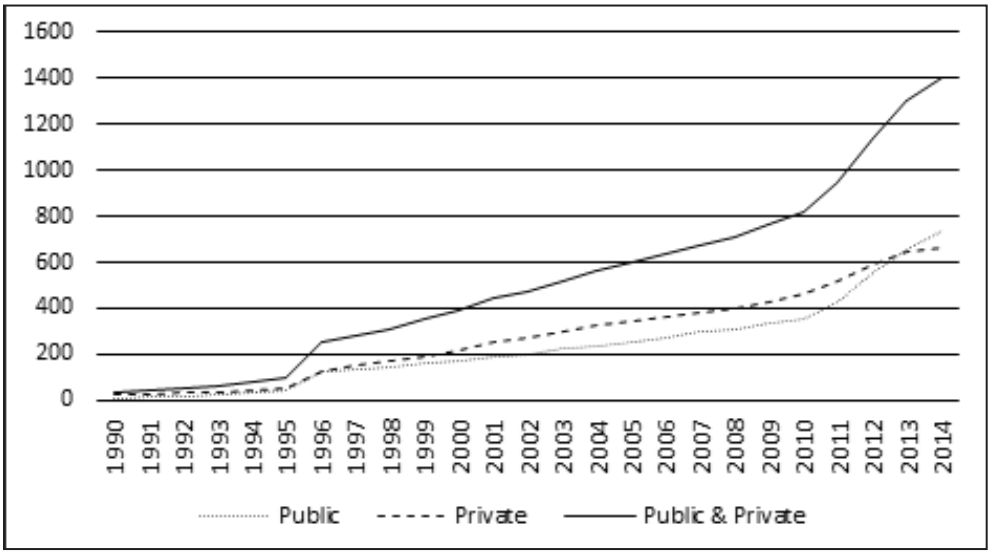
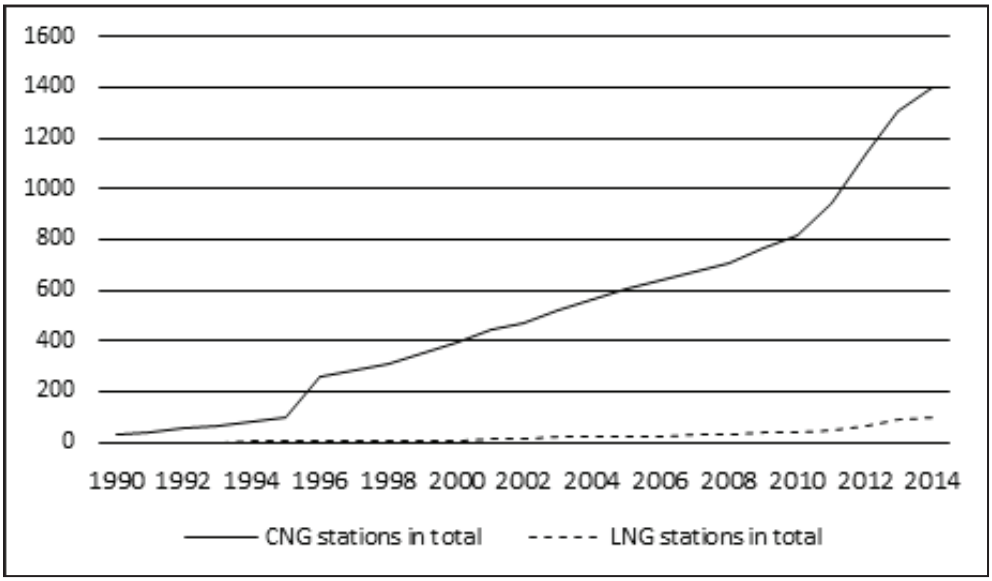



**Figure 2: Growth in US CNG and LNG Refueling Stations**




With respect to natural gas refueling stations in Texas, it is worth noting that Texas has never been the largest NGV market in the U.S., in part because of the relatively low prices of gasoline and diesel. By the end of 2013, there were 70 CNG stations (39 public CNG stations and 31 private CNG stations) and 12 LNG stations (eight public LNG stations and four private LNG stations) in Texas. By the summer of 2014, Texas had 85 CNG stations and 13 LNG stations. Among them, there are

51 public CNG stations and 34 private CNG stations, and nine public LNG stations and four private LNG stations. In other words, 60% of CNG stations and 69% of LNG stations are public stations in Texas.

LNG is mostly used for heavy duty trucks. However, there are more and lighter duty cars using CNG as fuel, as more CNG stations are being built. Figure 3 illustrates the growth of CNG stations in Texas and the distribution of public and private refueling stations over time. Figure 4 contrasts the growth rates of Texas CNG and LNG stations.

**Figure 3: Texas CNG Stations Growth and Distribution of Public vs. Private Stations**

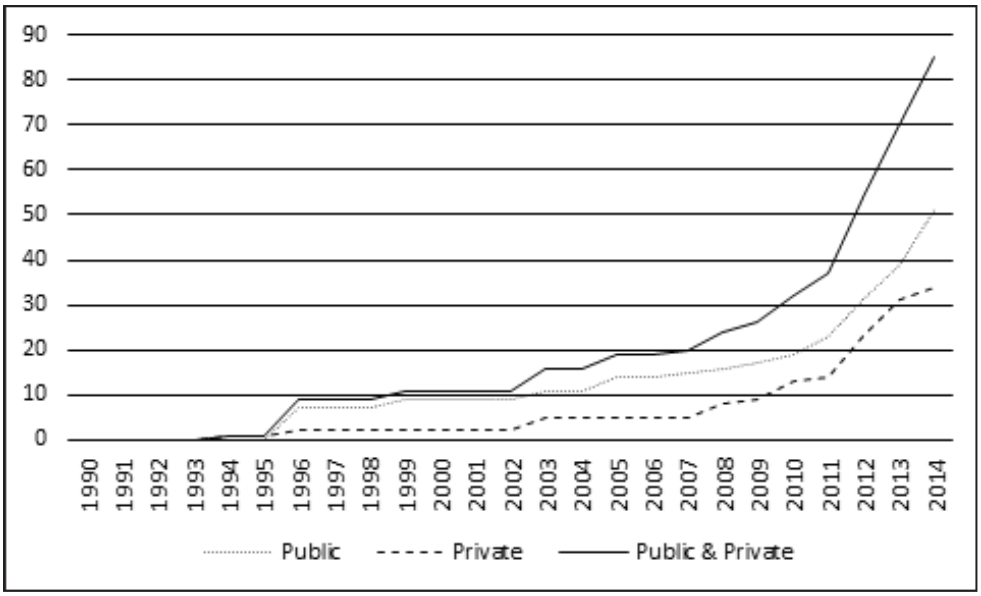
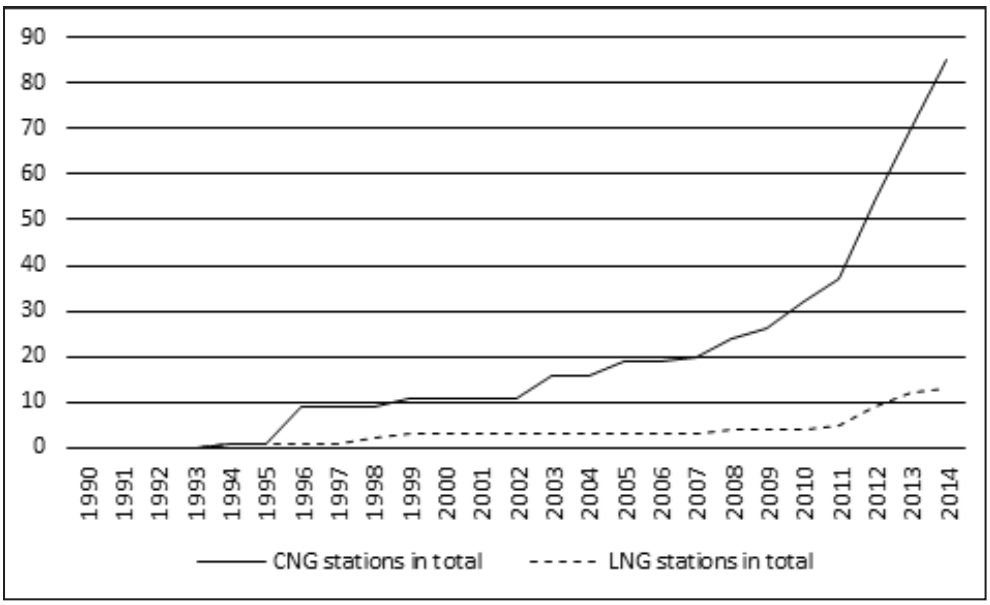



**Figure 4: Growth in Texas CNG and LNG Refueling Stations**



In summary, U.S. NGV adoption has been stable since 2003 at around 117,000 units, by measure of NGV registrations. The percentage of U.S. NGV adoption has remained at .04% or above over this time. For the Texas NGV market, the percentage of NGV adoption is slightly higher than overall U.S. adoption. Texas percentage has remained at .05% or above since 2003. With respect to natural gas refueling infrastructure, although the numbers of natural gas stations in the U.S. and Texas appear to be small, their numbers have been increasing at a steady pace. In particular, private refueling stations have had much stronger growth in recent years in both the United States and Texas markets. Stable NGV adoption and growing refueling infrastructure would seem to indicate that NGVs are slowly growing in fleet importance within AFVT markets.

## MODEL ESTIMATION AND RESULTS

These national and state data sets are used to estimate both Bass and GBass NGV technology diffusion models described earlier. Non-linear regression techniques are applied to estimate the coefficients of NGV technology adoption and diffusion models.

### U.S. NGV Diffusion Model Estimation

**Bass Model Estimation.** As the annual national NGV data distinguish CNG vehicles from LNG vehicles, we can perform Bass-based NGV diffusion estimates for both CNG vehicles and LNG vehicles, respectively. The numbers of CNG and LNG vehicles are combined to get national counts of total NGVs. Time values are assigned in accordance with the years when NGV data were available.

As mentioned, the values for the innovation parameter ($p$) and imitation parameter ($q$) are expected to be positive and significant. Initial values for these parameters are needed to run the Bass modeling on STATA. Referencing related studies by Becker et al. (2009) and McManus and Senter (2009), we initially assign the following values: $p = .01$ and $q = .5$.

Table 5 shows the Bass model estimates for our data on CNG vehicles, LNG vehicles, and total US NGV vehicles. In each model, note that respective $p$ values are smaller than their corresponding $q$ values, indicating that for this market imitation effects are stronger than innovation effects. In addition, the $p$ coefficients are not significant, but all $q$ coefficients in the models are positive and statistically significant. This finding suggests that potential NGV adopters in the U.S. are risk-averse and will typically commit to this technology purchase based on others' information and experience.

**Table 5: Estimation Results for Parameters in US NGV Bass Models**

| Parameters | Total NGVs | CNG Vehicles | LNG Vehicles |
|---|---|---|---|
| **m** | 115341.6 (22.05)*** | 112399.1 (22.00)*** | 2973.056 (29.58)*** |
| **p** | .0750829 (.88) | .076494 (.87) | .0343847 (1.51)† |
| **q** | .7856463 (1.92)* | .7982316 (.076)* | .5716242 (3.83)*** |

*** p< .001; ** p < .01; * p < .05; †p < .10 (1-tailed tests). *t values* in parentheses.

**Generalized Bass Model Estimation.** The GBass model for U.S. NGV penetration includes two additional marketing variables, whose choice was motivated by the relevant literature: natural gas fuel price per GGE (gasoline gallon equivalent) and the number of natural gas refueling stations nationwide. Natural gas fuel price effects are estimated by the coefficient $\beta_1$, while natural gas refueling infrastructure effects are evaluated by the coefficient $\beta_2$. To determine the initial values of $p$ and $q$, we again refer to Becker et al. (2009) and McManus and Senter (2009) and assign the values $p = .1$ and $q = .5$. We anticipate $\beta_1$ to be negative and significant since increasing prices have a negative effect on vehicle sales. In contrast, $\beta_2$ is expected to be positive and significant because a well-developed refueling infrastructure will encourage more NGV adoption.

Again, we utilize non-linear least squares to estimate our NGV GBass models. Table 6 shows the GBass model estimates for CNG vehicles, LNG vehicles, and total U.S. NGV vehicle models. In our three GBass models, respective values of *p* are smaller than their corresponding *q* values. These outcomes are similar to our basic Bass models in Table 5 and again show imitation effects here are stronger than innovation effects. Moreover, our *p* coefficients are not significant, but the *q* coefficients in all our GBass specifications are positive and statistically significant, buttressing our findings that this market is characterized by risk-averse purchasing behavior of potential adopters in U.S. NGV markets.

**Table 6: Estimation Results for Parameters in US NGV Generalized Bass Models**

| Parameters | Total NGVs | CNG Vehicles | LNG Vehicles |
|---|---|---|---|
| **m** | 123941.7 (35.60)*** | 120757.6 (35.76)*** | 3107.289 (29.32)*** |
| **p** | .0340352 (.55) | .0344995 (.54) | .0159096 (.36) |
| **q** | .2701521 (2.00)* | .2685476 (1.96)* | .4131224 (3.25)** |
| β1 | -.5722201 (-.15) | -.5275174 (-.14) | -.5328285 (-.22) |
| β2 | .6631471 (.71) | .6814265 (.72) | .1553682 (.15) |

*** p< .001; ** p < .01; * p < .05; †p < .10 (1-tailed tests). *t values* in parentheses.

The signs of $\beta_1$, the coefficient for natural gas fuel price per GGE, are negative. But surprisingly, the coefficients $\beta_1$ are not statistically significant in all our models. The signs of $\beta_2$, the coefficient for the number of NG refueling stations, are positive. But the coefficients $\beta_2$ are not statistically significant in all specifications. We speculate about these outcomes, which may result from several factors. First, most current NGV adopters are fleet owners, and various governments in the United States have used financial aids to incentivize NGV adoption. Secondly, NGV technologies are estimated to be more environmentally friendly and to generate less emission. As such, natural gas fuel price at this stage may not be a dominant factor for NGV adoption. Regarding the infrastructure effect, fleet owners, as primary NGV adopters, are more likely to build their own refueling facilities to sustain their NGV operations, so that the level of NGV adoption may be independent of the expansion of natural gas refueling infrastructure. In any case, our results are broadly comparable with the prior related results of McManus and Senter (2009), who found that only the imitation parameter was statistically significant.

### Texas NGV Diffusion Model Estimation

**Bass Model Estimation.** Bass models need a certain number of observations to ensure reliable estimation (Balakrishnan 2007). Small samples may lead to a long convergence time, or the model may not converge at all. For this research, the complete data sets for state-specific NGVs, fuel prices, and refueling stations each contain nine observations. Thus for our Texas NGV Bass models, STATA cannot converge. Alternatively, we use tools of MATLAB's Statistics and Machine Learning Toolbox (also used in recent technology diffusion literature) to run our non-linear regression models on this data (Lin and Lai 2012; Vodopivec and Herrmann 2012). MATLAB utilizes iterative least square estimation methods to estimate non-linear regression coefficients. MATLAB tools enumerate possible initial values to start new non-linear regressions and return a local optimum. The iterative processes continue and eventually identify global optimal estimates (MathWorks 2016a, 2016b).

Once again, in this specification, there are four unknown parameters: *p*, the coefficient of innovation; *q*, the coefficient of imitation; *M*, the maximum market size; and *Y*, the start year of the model. We assume here that *Y* is at 2003 (the first year in our data set). Non-linear regression estimation in MATLAB requires assigning an initial value for each parameter in the Bass model to

initiate the iterations. In order to avoid bias in conjectures about the initial values of the innovation and imitation coefficients ($p$ and $q$), maximum NGV market size ($M$), and the start year ($Y$) are assumed to be unknown parameters.

In spite of the small sample size, MATLAB achieves convergence. However, the codes developed by the modeler are not able to generate variances on the coefficients for hypotheses testing. Hence, the regression outputs reported here must be considered as exploratory outcomes. Table 7 summarizes point estimates of the unknown parameters for Texas NGV and CNG vehicle Bass models. Applying the estimates, the formal Bass adoption curves can be derived for both NGV and CNG vehicles' market penetration in Texas. The Bass curves for Texas NGV penetration are shown in Figures 5 and 6 below. The figures indicate the models' approximation (shown as "x" in the figure) and the historical data (shown as "o"), along with the particular S-shape curves derived from the estimates.

**Table 7: Estimation Results for Parameters in Texas NGV Bass Models**

| Parameters | Total NGVs | CNG Vehicles |
|---|---|---|
| ***M*** | 12000 | 12000 |
| ***p*** | .0000333582 | .000924284 |
| ***q*** | .999886 | .499358 |
| ***Y*** | 9.99 | 12.99 |

**Figure 5: Estimated Bass Curve for Texas NGV Penetration**

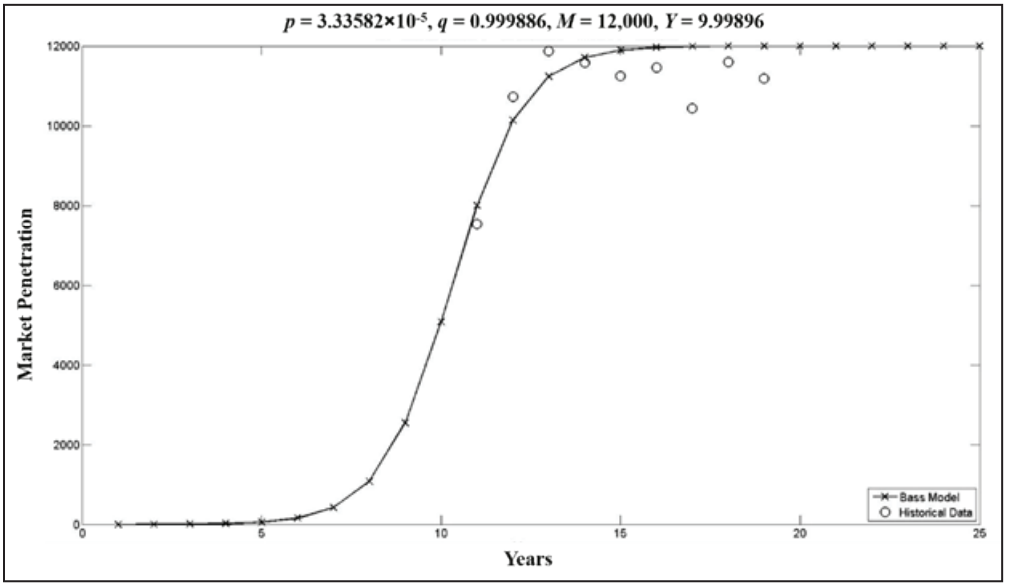
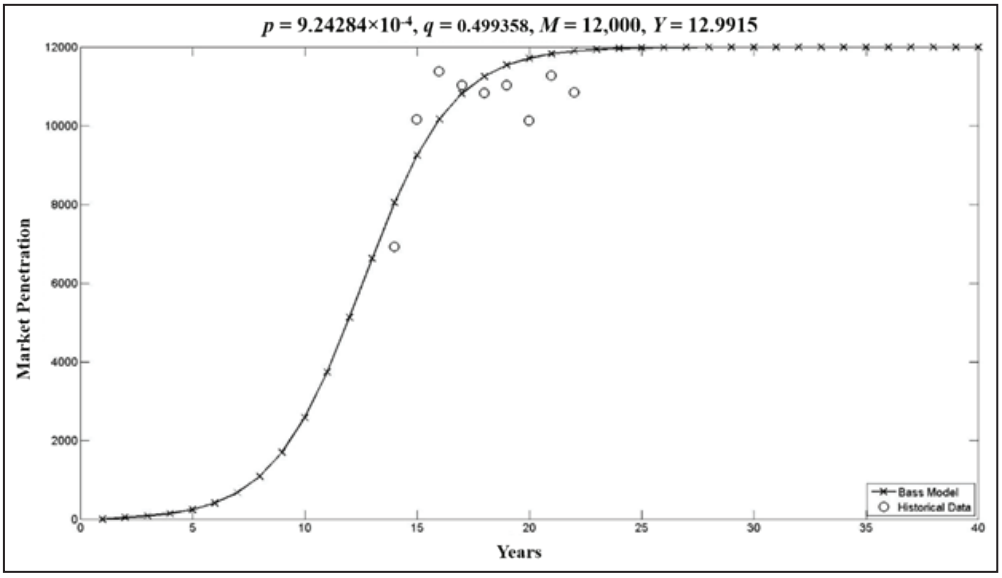


**Figure 6: Estimated Bass Curve for Texas CNG Vehicle Penetration**




## DISCUSSION

Researchers have observed that AFVT sales growth or market penetration reflects technology diffusion, and the nature of this process can be estimated by Bass and/or GBass models. Early AFVT research applied the Bass model to study hybrid electric vehicles diffusion, while Bass/GBass methods were subsequently utilized to forecast the diffusion of newer technologies, such as plug-in hybrid electric vehicles. This research extends Bass and GBass model applications within the modern AFVT literature.

One theme in AFVT diffusion studies is the challenge of data availability. Prior studies were conducted in early stages of AFVT adoption, and sometimes only a few observations exist from available sources. Furthermore, the early stages of technology introduction may cause fluctuations in market penetration due to factors like competitive dynamics, market inertia, technological failures, and so forth (Huo et al. 2012; Paltsev et al. 2011). As a result, the sales data needed to estimate Bass and GBass models may display nontrivial variation, generating insignificant estimates or even model non-convergence. This research also highlights an approach to estimate Bass/GBass models with extreme data constraints.

We use our NGV data to estimate Bass and GBass models of U.S. and Texas NGV diffusion. We find that NGV technologies now seem to be considered somewhat mature in the automobile industry. Adoption of both CNG and LNG vehicles seems to be increasingly common among vehicle fleets and the public.

By using statistical software that accounts for small sample issues, we show the limitations on estimating Bass diffusion models on smaller data sets can be overcome. The complete Texas-specific data set only contains nine observations, and this number is lower than the observational threshold typically used in empirical Bass studies. We use MATLAB and develop an exploratory exercise to illustrate that, by using appropriate software combined with non-linear least square regression tools, both the Texas Bass NGV and CNG vehicle models converge.

Among all U.S. and Texas Bass model runs, the $p$ and $q$ parameter estimates are similar. The $p$ values (innovation factors), are all much smaller than the $q$ values (imitation factors). The low $p$ values indicate that very few fleets or the public are likely to invest in such novel vehicle technology in either the U.S. or Texas automobile markets. On the other hand, imitation effects are observed in

NGV penetration, considering our estimated *q* values. Our *q* value suggests that "word of mouth" continues to be effective in promoting NGVs to fleets and the public. In turn, the estimates of signs and values of *p* and *q* are consistent with our expectations and those results documented in prior AFVT studies.

The U.S. GBass estimates provide insight into how natural gas fuel prices and available refueling stations affect extant NGV penetration. First, for the three specifications of all NGVs, CNG vehicles, and LNG vehicles, estimates of $\beta 1$, the coefficient of the natural gas fuel variable, are similar. The negative sign of $\beta 1$ suggests that higher natural gas fuel prices will negatively impact the growth of NGVs. In addition, the estimates of $\beta 2$, the coefficients of the number of natural gas refueling stations, are positive. This suggests that as more natural gas refueling stations are available to fleets and the public, there should be more adoption of NGVs.

Our estimates of the maximum number of NGV vehicles, represented by the values of the M parameters, are similar to recent NGV counts in our data. This implies that both the U.S. and Texas NGV markets may have reached a saturation level. These are surprising outcomes given the optimistic statements by NGV proponents who were informally interviewed during the project. Further, our findings appear to be somewhat contradictory to reports of emerging NGV markets that can be found in trade publications.

The discrepancy between our results and the apparent phenomenon of growing NGV markets may be explained by newly introduced bi-fuel engine technologies. Bi-fuel NGV technologies allow drivers to switch between natural gas and a conventional fuel, either diesel or gasoline. Indeed, the primary purpose of bi-fuel vehicles is to avoid the range problem that exists because of a lack of natural gas refueling infrastructure, allowing drivers' use of conventional fuels when desired or when natural gas fuels are not available.

As per the distinction between various types of electric vehicles (for example hybrid electric vehicles and plug-in hybrid electric vehicles), we offer that dedicated NGV and bi-fuel NGV diffusion processes may need to be analyzed separately. While NGV technologies are similar across the two types of vehicles, certain operational characteristics, i.e., need for maintenance, operational range, vehicle routing and scheduling plans, etc., may vary significantly between dedicated and bi-fuel NGVs. From both the current and potential NGV adopters' standpoint, dedicated and non-dedicated NGVs look to be considered as essentially different technologies.

## CONCLUDING REMARKS

Proponents of alternative fuels have offered natural gas as a major alternative transportation fuel for the United States in the near future. We know that the price spread between natural gas and conventional fuels, e.g., gasoline and diesel, has been widening over the last decade, meaning that U.S. fleets operating on natural gas can save fuel costs from one-half to two-thirds of conventional fuel costs. Environmentally, natural gas is also a clean-burning fuel. The potential of natural gas fuels to reduce pollutant emissions and greenhouse gases has led to governments increasing funding for NGV adoption, and has also motivated existing fleets to purchase or convert to NGVs.

Furthermore, adoption of NGV technology will also enhance energy independence in the United States by moving away from its traditional reliance on foreign oil and gas imports. The recent growth of domestic oil and gas exploration and production within the United States implies continued reductions in the need for foreign oil and gas. Since the transportation sector has been the largest energy user in the United States, continued growth of NGV adoptions in U.S. fleets as well as the public can help stimulate long-term natural gas production and help maintain a domestic natural gas fuel market.

Interestingly, our results indicate that NGV markets appeared to become saturated around the year 2010. This finding stands in contrast to anecdotal evidence about ongoing NGV adoption. In fact, promotional activities for CNG, LNG, and bi-fuel vehicle technologies were not widely

introduced to either fleets or the public until quite recently. Any increasing adoption of related technology motivated by promotional activities is not likely being captured in our data set.

In addition, newly adopted NGVs are equipped with so-called bi-fuel technologies, which allow drivers to switch between natural gas fuels and CNG or LNG. These bi-fuel NGVs are distinct from traditionally dedicated NGVs, since bi-fuel NGVs have fewer constraints on range and thus more flexibility in routing and scheduling arrangements. These features are similar to hybrid electric vehicles and reduce the risk of operation compared with traditional NGVs. This latter technology may motivate more acceptance among potential NGV adopters, but we do not distinguish between the two NGV engine configurations due to data availability. Future research should collect detailed data to examine whether the market penetrations will vary between dedicated and non-dedicated NGVs.

Finally, it should be noted that the empirical contribution of the present research pertains to the STATA-based model specifications. The MATLAB-based exercise is employed to makes it useful for the small set of Texas diffusion data and address the convergence problem in STATA runs. While STATA and MATLAB tools have appeared in technology diffusion literature, it is inconclusive that particular research tools, or newer versions of them, might overcome such shortfalls as estimation convergence with extremely limited data. In our view, future research may perform in-depth assessments regarding the effectiveness of extant research tools to model technology diffusions with data limitations. Furthermore, research that improves the efficiency of algorithms to specify diffusion models using limited data is in order.

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# Safety Impacts of Converting Two-Way Left-Turn Lanes to Raised Medians and Associated Design Concerns

**by Priyanka Alluri, Albert Gan, and Kirolos Haleem**

*Raised medians and two-way left-turn lanes (TWLTLs) are the two most common types of median treatments on arterial streets. This paper aims to conduct a detailed study on the safety impacts of conversion from TWLTLs to raised medians on state roads in Florida. In addition, the study also investigated several potential safety concerns related to raised medians on state roads, including crashes at median openings, vehicles directly hitting the median curb, and median crossover crashes. Based on data availability, 17.51 miles of urban arterial sections in Florida that were converted from TWLTLs to raised medians were analyzed. Police reports of all the crashes before and after median conversion were reviewed to correct miscoded crash types and obtain additional detailed crash information. Overall, a 28.5% reduction in total crash rate was observed after the 10 study locations were converted from TWLTLs to raised medians. The reductions in the proportions of left-turn and right-turn crashes were statistically significant, while the changes in the proportions of other crash types were not statistically significant. Furthermore, the crash data did not show evidence that raised medians are an additional hazard compared with TWLTLs.*

## INTRODUCTION

A two-way left-turn lane (TWLTL) is a continuous lane between opposing lanes of traffic to allow traffic to make left turns from both directions, and a raised median is a physical barrier that separates opposing lanes of traffic. TWLTLs reduce left turns from through lanes, provide operational flexibility for emergency vehicles, and give unrestricted access to abutting businesses and residences. On the other hand, they do not provide a pedestrian refuge area, increase head-on crashes, and operate poorly on high-traffic arterials. Compared to TWLTLs, raised medians provide a pedestrian refuge area, reduce head-on crashes, and reduce the number of conflicting maneuvers at driveways. However, they might increase crashes at median openings and limit direct access to properties (Koepke and Levinson 1992).

The Florida Department of Transportation (FDOT 2006) has had a policy to install raised medians in most new multilane highway projects since the 1990s. It requires "all multilane projects over 40 mph in design speed to have a restrictive median, and all other multilane facilities with design speeds ≤ 40 mph to include sections of raised median for enhancing vehicular and pedestrian safety, improving traffic efficiency, and attaining the standards of the Access Management Classification of that highway system" (FDOT 2006).

This FDOT policy was based on earlier study results showing the benefits of raised medians, as compared with TWLTLs. Several studies over the past two decades documented a reduction in crash rate after arterials with TWLTLs were converted to raised medians (Maze and Plazak 1997, Gluck et al. 1999, Gattis et al. 2005, Parsonson et al. 2000, Eisele and Frawley 2005). However, results from some more recent studies (for example, Phillips 2004, Schultz et al. 2007) showed an increase in crash rates after conversion from TWLTLs to raised medians. Phillips (2004) observed a higher proportion of fatal crashes at locations with raised medians compared with their TWLTL counterparts (0.55% versus 0.20%). Squires and Parsonson (1989) concluded that TWLTLs could be safer than raised medians on six-lane arterials with few concentrated access points. They also found that the safety performance of raised medians could be overestimated because of shifting of crashes to other surrounding intersections. Hence, the safety impacts of the conversion from TWLTLs to

raised medians have not been clear. This paper presents the results from a detailed study to evaluate the safety impacts of median conversion from TWLTLs to raised medians on state roads in Florida (Alluri et al. 2012). In addition, the study also investigated several potential safety concerns related to raised medians, including crashes that occur at median openings involving vehicles turning left and making U-turns, vehicles directly hitting the median curb, and median crossover crashes.

Information on how the crash had occurred is not available in the crash summary records, and could only be determined from a detailed review of police crash reports. As such, a major effort of this study was to review individual police reports of crashes that occurred before and after the median conversion. These police reports are a key to accurately determine the safety benefits of the median conversion and to investigate the safety concerns related to raised medians.

## EXISTING STUDIES

In a cross-sectional study based on statewide data from Florida, Long et al. (1993) found that urban four-lane arterials with raised medians experienced a 16.8% lower crash rate compared to those installed with TWLTLs. Papayannoulis et al. (1999) analyzed 264 roadway segments from Delaware, Illinois, Michigan, New Jersey, and Wisconsin and found that, compared with undivided arterials, TWLTLs had a 20% reduction in total crash rate, while raised medians had a 40% reduction. Mauga and Kaseko (2010) used multivariate regression analysis to relate geometric and access management features to traffic safety at midblock sections and found a 23.2% reduction in crash rate for raised medians compared with TWLTLs.

Dixon et al. (1999) concluded that the performance of raised medians is excellent except at locations with significant U-turn activity. However, contradicting statements were found in the literature. Bonneson and McCoy (1998) stated that improved safety and operational performance were a function of U-turn activity at intersections. Carter et al. (2005) concluded that U-turns did not have a large negative safety effect on signalized intersections. Levinson et al. (2005) also observed similar results for unsignalized intersections (i.e., at median openings).

Levinson et al. (2005) analyzed 806 unsignalized median openings in seven states and found that the urban arterial corridors experienced an average of 0.41 U-turn-plus-left-turn crashes per median opening per year; and rural arterial corridors experienced an average of 0.20 U-turn-plus-left-turn crashes per median opening per year. Zhou et al. (2003) conducted a four-year before-and-after analysis at a location that was converted from a traditional two-way opening to a directional median opening, and the results showed a 68% reduction in crashes with no additional crashes at the nearby median U-turn opening.

Based on the review of the existing literature on the safety performance of raised medians and TWLTLs, Bonneson and McCoy (1997) found that conversion from a TWLTL to a raised median reduced total crashes by about one-third. Gluck et al. (1999) summarized the findings of 16 studies that compared crash rates at undivided locations, locations with TWLTLs, and locations with raised medians. The authors reported six studies that had a decrease in sideswipe, angle, and head-on crashes averaging to 31%, 40%, and 54%, respectively. They also reported that the percent decrease in rear-end crashes ranged from −15% to 50% with an average of 27%. Lewis (2006) and Schultz et al. (2007) conducted before-and-after analyses to evaluate the safety effectiveness of raised medians over TWLTLs, and reported mixed results. The authors concluded that raised medians did not reduce total crash rates, but reduced angle, fatal, and injury crash rates. Lewis (2006) observed that higher signal density might have contributed to an increase in rear-end crashes after median construction. More recently, Mauga and Kaseko (2010) used multivariate regression models to develop relationships between access management features and crash rates by crash severity, crash type, and total crashes. The authors concluded that the conversion from a TWLTL to a raised median resulted in a reduction in all types of crashes except single-vehicle crashes.

Parsonson et al. (1993) evaluated the safety performance of a 4.34-mile six-lane arterial section on Memorial Drive, Dekalb County, Georgia, which was converted from a TWLTL to a raised median. The improvement was estimated to have prevented about 300 crashes and about 150

injuries in a one-year period. The authors also observed a 37% and 48% reduction in total and injury crash rates, respectively. Maze and Plazak (1997) evaluated the safety effect of conversion from a TWLTL to a raised median in the cities of Ankeny and Clive in Iowa. They found that crash rates reduced by 36.5% and 41.7% in the two cities, respectively. Bonneson and McCoy (1997) criticized that these results were from studies that do not account for the regression-to-the-mean (RTM) effect and, therefore, the actual reduction in crashes could be up to 15% less depending on the analysis period and crash frequency.

Recent studies have accounted for the RTM bias by using advanced Bayesian analyses. Lyon et al. (2008) evaluated the safety effectiveness of TWLTLs based on before-and-after analysis using the empirical Bayes (EB) approach. Based on a 95% significance level, the authors concluded that reductions of at least 29%, 36%, and 19% can be expected in total, rear-end, and injury crashes, respectively, when TWLTLs are installed at rural sections. Schultz et al. (2011) used the hierarchical Bayesian approach to evaluate the safety performance of raised medians. After installing raised medians, crash frequencies of total and severe injury crashes reduced by 39% and 44%, respectively.

In summary, studies have shown different reductions and distributions by crash severities and crash types, and different correlations among the geometric characteristics of roads. These studies have often produced contradictory results, most likely due to one or more of the following reasons: high variability in crash data, variations in crash reporting thresholds, fewer number of crashes, inconsistencies in the target crash types identified for the analysis, and differences in the analytical approaches (e.g., before-and-after analysis versus cross-sectional analysis) (Bonneson and McCoy 1997).

## DATA PREPARATION

This section describes the efforts undertaken to identify urban arterials where TWLTLs were converted to raised medians. It also discusses the police report review process. Police reports were reviewed to verify and correct miscoded crash types and to determine how the crash occurred from the illustrative sketches and descriptions.

### Identify Study Locations

FDOT's Roadway Characteristics Inventory (RCI) database was used to identify urban arterials with raised medians that were converted from TWLTLs. Study locations were identified by comparing the segments with TWLTLs in the 2005 RCI database with the segments with raised medians in the 2010 RCI database.

A total of 2,675 segments with TWLTLs were extracted from the 2005 RCI database, and 2,597 segments with raised medians were extracted from the 2010 RCI database. The two extracted datasets were then matched based on the median change. Since many smaller segments were generated, they were aggregated into longer segments based on 2010 data. As a result, a total of 225 roadway segments that were converted from a TWLTL to a raised median were identified. Segments shorter than 200 feet and those on non-state roads were excluded. Finally, a total of 78 segments were considered for further analysis. The median construction periods of the 78 roadway segments were requested from the FDOT district offices to determine the before and after periods for analysis. Construction dates were available for 35 locations.

Locations with at least 24 months of crash data before and after the median construction were included in the before-and-after safety analysis. In addition, one month prior to the start of the construction period and three months after the end of the construction period were excluded considering potential pre-construction activities and the fact that some drivers may need time to adjust to the new treatment and resume normal travel patterns. As such, a total of 10 locations were found to have at least two years of before and after analysis periods, and were included in the before-and-after safety analysis. In addition, a total of 18 locations with at least 12 months of data

after the construction of raised medians were used to evaluate potential design concerns associated with raised medians.

### Review Police Reports

FDOT's Crash Analysis Reporting (CAR) system was used to identify crashes that occurred at the study locations. Since the police reports were available only from January 2003 to December 2010, only the locations with a construction period between February 2005 and September 2008 were included in the before-and-after analysis. Also, when available, a maximum of 36 months of crash data before and after construction were used. Based on these criteria, 10 locations were selected for before-and-after analysis. Police reports of crashes that occurred at these 10 locations were downloaded from the Hummingbird web system hosted on FDOT's Intranet. Based on the illustrations and descriptions available in the police reports, the correct crash type was recorded and used in the analysis.

Overall, crash type was corrected for 18.7% of the crashes. Table 1 gives the distribution of the coded and corrected crash type for the most common crash types. For example, it shows that police officers identified 676 angle crashes in the reports. However, through review of the illustrative sketches and descriptions in the police reports, only 402 were identified as having been correctly coded as angle crashes, while the remaining 274 crashes should have been coded as head-on (3), left-turn (183), median crossover (4), rear-end (22), right-turn (33), and sideswipe (29). Similarly, police officers had coded 100 head-on crashes. However, only 25 were correctly coded as head-on, while the remaining 75 were actually angle (20), left-turn (15), median crossover (3), rear-end (35), and right-turn (2). After all the crash types were corrected, for example, there were a total of 560 angle crashes (instead of 676), including 402 (or 71.8%) that were correctly coded and 158 (or 28.2%) that were corrected.

**Table 1: Distribution of the Coded and Corrected Crash Type**

| | | **Crash Type Coded in Police reports** | | | | | | | Total Crashes **WITH** Corrected Crash Type | Percent Corrected |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Angle | Head-On | Left-Turn | Median Crossover | Rear End | Right-Turn | Side-swipe | | |
| **Corrected Crash Type** | Angle | 402 | 20 | 38 | - | 37 | 5 | 58 | 560 | 28.2% |
| | Head-On | 3 | 25 | - | - | - | - | - | 28 | 10.7% |
| | Left-Turn | 183 | 15 | 334 | - | 4 | - | 21 | 557 | 40.0% |
| | Median Crossover | 4 | 3 | 1 | 7 | 2 | - | 2 | 19 | 63.2% |
| | Rear-End | 22 | 35 | 1 | - | 1,486 | 1 | 12 | 1,557 | 4.6% |
| | Right-Turn | 33 | 2 | - | - | 10 | 45 | 17 | 107 | 57.9% |
| | Sideswipe | 29 | - | 6 | - | 6 | 2 | 189 | 232 | 18.5% |
| Total Crashes **WITHOUT** Corrected Crash Type | | 676 | 100 | 380 | 7 | 1,545 | 53 | 299 | 3,060 | 18.7% |

Table 1 also shows that 63.2% of the median crossover crashes were coded incorrectly, followed by right-turn and left-turn crashes at 57.9% and 40.0%, respectively. Of the 107 right-turn crashes, 33 were incorrectly coded by police officers as angle crashes. Similarly, 183 of 557 left-turn crashes were incorrectly coded as angle crashes. Likewise, 7 of 19 median crossover crashes were incorrectly coded as either angle or head-on crashes.

## BEFORE-AND-AFTER ANALYSIS

This section discusses the results from the before-and-after analysis conducted based on crash type, crash severity, and facility type. Table 2 provides the summary statistics by study location. The table

also provides the crash rates for both the before and after periods. Equation (1) gives the formula used to calculate crash rate in crashes per million vehicle miles traveled.

$$(1)\quad Crash\ Rate = \frac{Total\ Crashes \times 10^6}{AADT \times Segment\ Length \times Analysis\ Period\ in\ Years}$$

**Table 2: Summary Statistics by Study Location**

| S No. | Roadway ID | Segment Length (mi) | No. of Lanes | Posted Speed Limit | Before | | | | After | | | | Percent Change in Crash Rate |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Period[a] | No. of Crashes | Mean AADT | Crash Rate[b] | Period[a] | No. of Crashes | Mean AADT | Crash Rate[b] | |
| 1[c,d] | 93130000 | 0.290 | 4 | 35 | 36 | 15 | 18,340 | 2.576 | 30 | 15 | 18,887 | 3.001 | 17% |
| 2[d] | 58010000 | 0.260 | 2 | 55 | 19 | 5 | 11,560 | 2.879 | 35 | 13 | 10,454 | 4.493 | 56% |
| 3[d] | 94010000 | 0.910 | 4 | 40 | 36 | 86 | 38,930 | 2.217 | 15 | 26 | 34,154 | 1.834 | -17% |
| 4[d] | 36004000 | 0.314 | 4 | 35 | 36 | 24 | 36,625 | 1.906 | 17 | 3 | 23,000 | 0.803 | -58% |
| 5[c,d] | 2030000 | 0.252 | 6 | 45 | 36 | 21 | 31,524 | 2.414 | 36 | 1 | 27,500 | 0.132 | -95% |
| 6[c,d] | 10030000 | 0.295 | 6 | 45 | 36 | 98 | 57,020 | 5.321 | 32 | 30 | 49,850 | 2.096 | -61% |
| 7[c,d] | 10030000 | 0.485 | 6 | 45 | 36 | 152 | 56,424 | 5.073 | 32 | 74 | 51,101 | 3.068 | -40% |
| 8[c,d] | 10030000 | 0.480 | 6 | 45 | 36 | 103 | 50,301 | 3.896 | 32 | 55 | 45,473 | 2.589 | -34% |
| 9[c,d] | 17040000 | 3.584 | 6 | 45 | 36 | 331 | 50,239 | 1.679 | 36 | 251 | 46,992 | 1.361 | -19% |
| 10[c,d] | 48070000 | 0.524 | 6 | 35 | 27 | 71 | 35,690 | 4.623 | 36 | 62 | 39,516 | 2.734 | -41% |
| 11[c,d] | 55002000 | 0.948 | 6 | 45 | 32 | 204 | 27,093 | 8.160 | 36 | 85 | 26,224 | 3.122 | -62% |
| 12[c,d] | 55060000 | 1.019 | 4 | 45 | 26 | 40 | 31,725 | 1.565 | 36 | 111 | 27,234 | 3.653 | 134% |
| 13[c,d] | 55080000 | 1.517 | 4 | 45 | 24 | 144 | 31,394 | 4.142 | 36 | 158 | 29,889 | 3.182 | -23% |
| 14[d] | 75003000 | 2.417 | 6 | 45 | 36 | 832 | 54,338 | 5.785 | 22 | 351 | 49,732 | 4.364 | -25% |
| 15[d] | 75010000 | 1.357 | 6 | 50 | 14 | 95 | 49,100 | 3.348 | 36 | 160 | 48,638 | 2.214 | -34% |
| 16[d] | 87030000 | 1.204 | 4 | 35 | 21 | 145 | 43,200 | 4.364 | 36 | 135 | 44,985 | 2.276 | -48% |
| 17[d] | 87090000 | 1.268 | 6 | 40 | 21 | 115 | 51,787 | 2.742 | 36 | 181 | 53,163 | 2.452 | -11% |
| 18[d] | 72014000 | 0.388 | 4 | 35 | 14 | 37 | 50,122 | 4.468 | 36 | 93 | 50,925 | 4.298 | -4% |

[a] Analysis period is in months.
[b] Crash rate is in crashes per million vehicle miles traveled (MVM).
[c] Location is included in before-and-after analysis.
[d] Location is included in evaluating the design concerns associated with raised medians.

An observational before-and-after evaluation study discussed in the Highway Safety Manual (HSM) was used to assess whether the construction of raised medians resulted in a shift in the frequency of a specific crash type as a proportion of total crashes. Consistent with the HSM, the Wilcoxon Signed Rank test was used to assess whether or not the conversion from TWLTLs to raised medians resulted in a shift in the frequency of each specific crash type and crash severity level as a proportion of total crashes (American Association of State Highways and Transportation Officials [AASHTO] 2010).

It is noted here that only the simple before-and-after method is needed in this study, as TWLTLs on state roads in Florida have been systematically converted to raised medians based on FDOT policy (FDOT 2006). In other words, the locations used in this study were not subject to the RTM bias as they were not selected for median conversion based on high crash experience.

## Crash Type

Table 3 gives the before-and-after study results by crash type. The reductions in the proportions of left-turn and right-turn crashes were statistically significant at 89.4% confidence level. The changes in the proportions of the other crash types, namely, head-on, rear-end, angle, side-swipe, and pedestrian crashes, were not statistically significant. Before-and-after crash statistics on median crossover crashes were not provided as the analysis does not yield meaningful results. Very few crashes in the before period were coded as "median crossovers" because of the absence of a median (i.e., a physical barrier) in the before period.

Overall, the total crash rate across all 10 locations reduced from 3.04 crashes per million vehicle miles traveled to 2.18 crashes per million vehicle miles traveled after median conversion, representing a 28.5% reduction. A reduction in crash rate was observed for all the major crash types, including head-on, rear-end, angle, left-turn, right-turn, sideswipe, and pedestrian crashes. The pedestrian crash rate statistics must be interpreted with caution as pedestrian exposure was not considered while calculating pedestrian crash rate.

**Table 3: Summary Statistics by Crash Type**

| Crash Type | Before Period | | | After Period | | | Percent Change in Crash Rate | Is the Change in Proportion of Crashes Statistically Significant?[d] |
|---|---|---|---|---|---|---|---|---|
| | Crash Freq.[a] | Crash Rate[b] | Proportion of Crashes[c] | Crash Freq.[a] | Crash Rate[b] | Proportion of Crashes[c] | | |
| Head-On | 0.32 | 0.02 | 0.007 | 0.14 | 0.01 | 0.005 | -49.9% | No (90.6%) |
| Rear-End | 17.80 | 1.15 | 0.379 | 13.22 | 0.94 | 0.433 | -18.2% | No (90.2%) |
| Angle | 7.25 | 0.47 | 0.15 | 5.00 | 0.36 | 0.16 | -24.1% | No (89.4%) |
| Left-Turn | 9.68 | 0.63 | 0.206 | 3.58 | 0.26 | 0.118 | -59.2% | Yes (89.4%) |
| Right-Turn | 1.95 | 0.13 | 0.042 | 0.80 | 0.06 | 0.026 | -55.0% | Yes (89.4%) |
| Sideswipe | 2.75 | 0.18 | 0.059 | 1.92 | 0.14 | 0.063 | -23.1% | No (90.2%) |
| Pedestrian | 1.08 | 0.07[e] | 0.023 | 0.83 | 0.06[e] | 0.027 | -14.7% | No (90.2%) |
| Total[f] | 46.95 | 3.04 | 1.000 | 30.49 | 2.18 | 1.000 | -28.5% | Not Applicable |

[a] Crash frequency is in crashes per mile per year.
[b] Crash rate is in crashes per million vehicle miles traveled.
[c] Proportion of observed crashes of a specific target collision type is calculated relative to total crashes across the entire analysis period.
[d] Wilcoxon signed rank test was used to determine whether or not the shifts in proportions for target collision types were statistically significant. The percentage in parentheses gives the confidence level.
[e] Pedestrian exposure was not taken into consideration while calculating pedestrian crash rate.
[f] Total crashes include all crash types.

## Crash Severity

Table 4 gives the before-and-after study results by crash severity. A reduction in the proportion of property damage only (PDO) crashes and an increase in the proportion of injury crashes were observed after raised median conversion; however, these results were not statistically significant. In terms of crash rate, a reduction in crash rate after raised median conversion was observed at both PDO and injury crash severity levels. PDO crash rate had the largest reduction (35.1%) while injury crash rate had the smallest reduction (22.1%).

**Table 4: Summary Statistics by Crash Severity**

| Crash Severity | Before Period | | | After Period | | | Percent Change in Crash Rate | Is the Change in Proportion of Crashes Statistically Significant?[d] |
|---|---|---|---|---|---|---|---|---|
| | Crash Freq.[a] | Crash Rate[b] | Proportion of Crashes[c] | Crash Freq.[a] | Crash Rate[b] | Proportion of Crashes[c] | | |
| PDO | 23.78 | 1.54 | 0.51 | 13.98 | 1.00 | 0.46 | -35.1% | No (89.4%) |
| Injury | 22.94 | 1.49 | 0.49 | 16.26 | 1.16 | 0.53 | -22.1% | No (89.4%) |
| Fatal | 0.24 | 0.02 | 0.01 | 0.25 | 0.02 | 0.01 | 0.0% | No (89.0%) |
| Fatal and Injury | 23.18 | 1.50 | 0.49 | 16.51 | 1.18 | 0.54 | -21.3% | No (89.4%) |
| Total[e] | 46.95 | 3.04 | 1.00 | 30.49 | 2.18 | 1.00 | -28.3% | Not Applicable |

[a] Crash frequency is in crashes per mile per year.
[b] Crash rate is in crashes per million vehicle miles traveled.
[c] Proportion of observed crashes of a specific target collision type is calculated relative to total crashes across the entire analysis period.
[d] Wilcoxon signed rank test was used to determine whether or not the shifts in proportions for target collision types were statistically significant. The percentage in parentheses gives the confidence level.
[e] Total crashes include all crash types.

## Facility Type

A total of 2.826 miles of four-lane urban arterials and 6.568 miles of six-lane urban arterials were converted from TWLTLs to raised medians. Of the 10 study locations, three are four-lane urban arterials, while the remaining seven are six-lane arterials. Table 5 gives crash summary statistics by crash type and crash severity at four-lane and six-lane facilities. Again, the observational before-and-after study considering the shift of proportions was performed to determine if the proportion of crashes after the median construction was significantly different from the proportion of crashes before the median construction for each crash type and severity level for both four-lane and six-lane facilities. Wilcoxon Signed Rank test was conducted to determine whether or not the shifts in proportions for target collision types were statistically significant. Note that this test was not conducted for four-lane facilities since only three four-lane facilities were analyzed, and the sample size is too small to perform the test. None of the shifts in crash proportions on six-lane facilities were found to be statistically significant except left-turn crashes.

After the conversion from TWLTLs to raised medians, six-lane arterials experienced a 39.3% reduction in total crash rate while four-lane arterials experienced an 11% increase in total crash rate. On six-lane sections, a reduction in crash rate was observed in all major crash types, namely, head-on, rear-end, angle, left-turn, right-turn, sideswipe, and pedestrian crashes. On the other hand, four-lane arterials yielded mixed results as a reduction was observed in left-turn, right-turn, and sideswipe crash rates, and an increase was observed in rear-end, angle, and pedestrian crash rates. In terms of crash severity, six-lane arterials experienced reductions in both PDO and injury crash rates, and no change in fatal crash rates, while four-lane sections experienced reductions in PDO and fatal crash rates, and an increase in injury crash rate.

**Table 5: Summary Crash Statistics at Four-Lane and Six-Lane Urban Arterials**

| | Four-Lane Facility | | | | | | | | Six-Lane Facility | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Before Period | | | After Period | | | Percent Change in Crash Rate | Is the Change in Prop. of Crashes Stat. Sig.?[d] | Before Period | | | After Period | | | Percent Change in Crash Rate | Is the Change in Prop. of Crashes Stat. Sig.?[d] |
| | Crash Freq.[a] | Crash Rate[b] | Prop. of Crashes[c] | Crash Freq.[a] | Crash Rate[b] | Prop. of Crashes[c] | | | Crash Freq.[a] | Crash Rate[b] | Prop. of Crashes[c] | Crash Freq.[a] | Crash Rate[b] | Prop. of Crashes[c] | | |
| **Crash Type** | | | | | | | | | | | | | | | | |
| Head-On | 0.00 | 0.00 | 0.00 | 0.12 | 0.01 | 0.00 | -- | --[e] | 0.42 | 0.02 | 0.01 | 0.16 | 0.01 | 0.01 | -50.0% | No (87.6%) |
| Rear-End | 10.31 | 0.95 | 0.32 | 16.45 | 1.61 | 0.48 | 69.5% | --[e] | 20.21 | 1.20 | 0.39 | 11.83 | 0.76 | 0.41 | -36.7% | No (90.2%) |
| Angle | 4.26 | 0.39 | 0.13 | 5.76 | 0.56 | 0.17 | 43.6% | --[e] | 8.21 | 0.49 | 0.16 | 4.67 | 0.30 | 0.16 | -38.8% | No (89.0%) |
| Left-Turn | 6.06 | 0.56 | 0.19 | 3.60 | 0.35 | 0.11 | -37.5% | --[e] | 10.84 | 0.64 | 0.21 | 3.58 | 0.23 | 0.12 | -64.1% | Yes (89.0%) |
| Right-Turn | 1.96 | 0.18 | 0.06 | 0.48 | 0.05 | 0.01 | -72.2% | --[e] | 1.95 | 0.12 | 0.04 | 0.93 | 0.06 | 0.03 | -50.0% | No (89.0%) |
| Side swipe | 1.80 | 0.17 | 0.06 | 0.96 | 0.09 | 0.03 | -47.1% | --[e] | 3.05 | 0.18 | 0.06 | 2.33 | 0.15 | 0.08 | -16.7% | No (89.0%) |
| Ped. | 0.33 | 0.03[f] | 0.01 | 0.60 | 0.06[f] | 0.02 | 100.0% | --[e] | 1.32 | 0.08[f] | 0.03 | 0.93 | 0.06[f] | 0.03 | -25.0% | No (90.6%) |
| Total[g] | 32.57 | 3.01 | 1.00 | 34.09 | 3.34 | 1.00 | 11.0% | NA[j] | 51.58 | 3.05 | 1.00 | 28.94 | 1.85 | 1.00 | -39.3% | NA[j] |
| **Crash Severity** | | | | | | | | | | | | | | | | |
| PDO | 15.38 | 1.42 | 0.47 | 14.17 | 1.39 | 0.42 | -2.1% | --[e] | 26.47 | 1.57 | 0.51 | 13.90 | 0.89 | 0.48 | -43.3% | No (89.0%) |
| Injury | 17.02 | 1.57 | 0.52 | 19.81 | 1.94 | 0.58 | 23.6% | --[e] | 24.84 | 1.47 | 0.48 | 14.73 | 0.94 | 0.51 | -36.1% | No (89.0%) |
| Fatal | 0.16 | 0.02 | 0.01 | 0.12 | 0.01 | 0.00 | -50.0% | --[e] | 0.26 | 0.02 | 0.01 | 0.31 | 0.02 | 0.01 | 0.0% | No (87.6%) |
| F+I[h] | 17.18 | 1.59 | 0.53 | 19.93 | 1.95 | 0.58 | 22.6% | --[e] | 25.11 | 1.49 | 0.49 | 15.04 | 0.96 | 0.52 | -35.6% | No (89.0%) |
| Total[i] | 32.57 | 3.01 | 1.00 | 34.09 | 3.34 | 1.00 | 11.0% | NA[j] | 51.58 | 3.05 | 1.00 | 28.94 | 1.85 | 1.00 | -39.3% | NA[j] |

a Crash frequency is in crashes per mile per year; b crash rate is in crashes per million vehicle miles traveled; c proportion of observed crashes of a specific target collision type is calculated relative to total crashes across the entire analysis period; d Wilcoxon signed rank test was used to determine whether or not the shifts in proportions for target collision types were statistically significant. The percentage in parentheses gives the confidence level; e sample size is too small to conduct the Wilcoxon signed rank test; f pedestrian exposure was not taken into consideration while calculating pedestrian crash rate; g total crashes includes all crash types; h fatal and injury; i total crashes is the sum of PDO, injury, and fatal crashes; j not applicable.

## EVALUATION OF SAFETY CONCERNS

This section focuses on the following three potential safety concerns related to raised medians: crashes that occur at median openings involving vehicles turning left and making U-turns, vehicles that hit the median curb, and median crossover crashes.

### Crashes at Median Openings

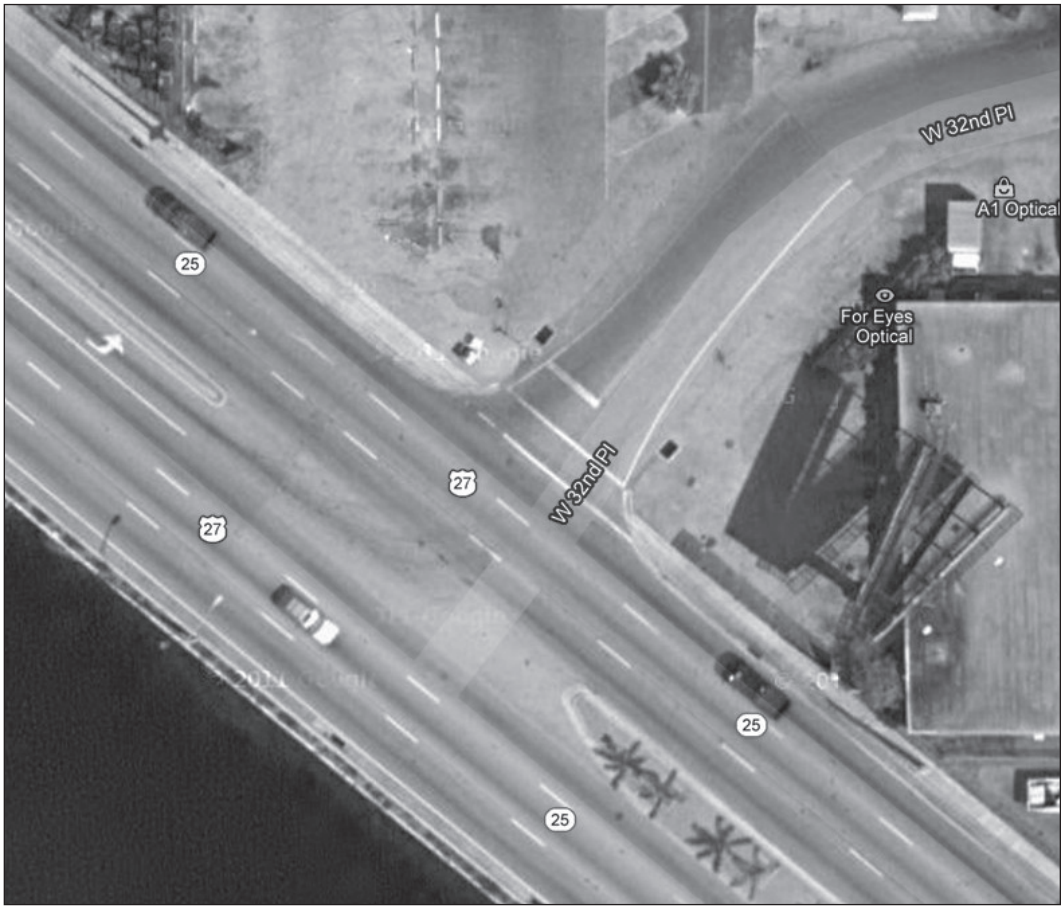
The 18 study locations have the following four types of median openings, as shown in Figures 1 through 4, respectively: uni-directional median opening (Figure 1), bi-directional median opening with center island (Figure 2), full median opening with left-turn bays in both directions (Figure 3), and full median opening with left-turn bay in one direction (Figure 4).

**Figure 1: Uni-directional Median Opening**


**Figure 2: Bi-directional Median Opening with Center Island**

**Figure 3: Full Median Opening with Left-turn Bays in Both Directions**


**Figure 4: Full Median Opening with Left-turn Bay in One Direction**



For each location, crashes that occurred at median openings after the location was converted from a TWLTL to a raised median were identified by reviewing police reports, and only those that could be attributed directly to the median opening were included in this analysis. For example, crashes involving vehicles making a U-turn or left-turn at median openings and crashes involving vehicles making a left turn from a side street were identified as median opening related crashes. Table 6 gives the crash rates at four-lane and six-lane facilities by median opening types. In this table, for each facility type, crash rate was calculated as the number of crashes related to median openings per exposure [as shown in Equation (2)], where exposure is the total number of median openings multiplied by the number of years from conversion date to December 2010.

$$(2)\quad Crash\ Rate = \frac{(Total\ \#\ of\ median - opening - related\ crashes)}{(Total\ \#\ of\ median\ openings \times Analysis\ period\ in\ years)}$$

**Table 6: Crash Rates at Median Openings by Opening Type and Roadway Facility**

| Median Opening Type | Four-Lane Facility | | | Six-Lane Facility | | |
|---|---|---|---|---|---|---|
| | No. of Crashes | No. of Median Openings | Crash Rate[a] | No. of Crashes | No. of Median Openings | Crash Rate[a] |
| Uni-directional median opening | 3 | 8 | **0.114** | 13 | 14 | **0.273** |
| Bi-directional median opening with center island | 3 | 5 | **0.182** | 30 | 14 | **0.630** |
| Full median opening with left-turn bay in one direction | 7 | 5 | **0.424** | 14 | 3 | **1.373** |
| Full median opening with left-turn bays in both directions | 14 | 5 | **0.848** | 43 | 5 | **2.529** |

[a] Crash rate is in median opening related crashes/median opening/year.

In total, 5.54 miles of four-lane urban arterials have 23 median openings, and 11.72 miles of six-lane urban arterials have 36 median openings. A uni-directional median opening on a four-lane facility was found to be the safest alternative for left-turning movements with a crash rate of 0.114 median opening related crashes/median opening/year. Not surprisingly, among the four median opening types, a full median opening with left-turn bays in both directions was the least safe alternative for left-turning movements. For a four-lane facility, the crash rate at this median opening type (0.848 median opening related crashes/median opening/year) is over seven times the crash rate at a uni-directional median opening (0.114 median opening related crashes/median opening/year). Among the three other types of median openings, a bi-directional median opening with center island was found to be the safest alternative for left-turning movements. Crash rates at median openings on four-lane and six-lane facilities were found to have a similar pattern.

In summary, the crash data show evidence that at both four-lane and six-lane facilities, uni-directional median openings provide a relatively safe alternative for left-turning movements. At locations where bi-directional/full median opening is warranted, a bi-directional median opening with center island has fewer median opening related crashes.

### Vehicles Hitting the Median Curb

On roadways with TWLTLs, errant vehicles have the opportunity to regain control before hitting an obstacle or an oncoming vehicle. However, raised medians often do not provide enough lateral clearance for errant vehicles. Therefore, one of the safety concerns of constructing raised medians is the frequency of vehicles that directly hit the median curb before stopping or resulting in secondary crashes primarily involving vehicles in opposite travel lanes.

Of the 2,436 crashes that occurred at the 18 locations from median construction December 2010, 48 (2.0%) involved vehicles directly hitting a median curb. Of these 48, 26 (54.2%) were PDOs while the remaining 22 (45.8%) resulted in an injury; there were no fatal crashes. When drug/alcohol involvement was examined, 39 (81.2%) did not involve alcohol/drugs while nine (18.8%) involved driving under influence (DUI). Table 7 gives summary statistics by crash location and crash severity at four-lane and six-lane facilities. About one-third of these crashes (31.3%) occurred near signalized intersections and the rest occurred at midblock locations. Compared with four-lane facilities, a slightly lower percentage of these crashes occurred at mid-block locations on six-lane facilities. In terms of crash severity, four-lane urban arterials experienced a higher percentage of injury crashes compared with six-lane facilities (67% vs. 41%). From these crash statistics, it is evident that those involving vehicles hitting a raised median were more severe on four-lane facilities.

**Table 7: Crash Statistics of Vehicles Hitting the Raised Median Curb**

| | Four-lane Facilities | | Six-lane Facilities | | Total | |
|---|---|---|---|---|---|---|
| | No. of Crashes | Percent of Crashes | No. of Crashes | Percent of Crashes | No. of Crashes | Percent of Crashes |
| **Crash Location** | | | | | | |
| Signalized Intersection | 2 | 22% | 13 | 33% | 15 | 31% |
| Midblock Location | 7 | 78% | 26 | 67% | 33 | 69% |
| **All Locations** | **9** | **100%** | **39** | **100%** | **48** | **100%** |
| **Crash Severity** | | | | | | |
| PDO | 3 | 33% | 23 | 59% | 26 | 54% |
| Injury | 6 | 67% | 16 | 41% | 22 | 46% |
| Fatal | 0 | 0% | 0 | 0% | 0 | 0% |
| **Total** | **9** | **100%** | **39** | **100%** | **48** | **100%** |

### Median Crossover Crashes

A median crossover crash occurs if an errant vehicle crosses a raised median and reaches an opposite travel lane at any point during a crash. Although crash reports have a code for "median crossovers" based on the first harmful event, not all crashes where the vehicle crossed over a median are identified as "median crossovers." For example, a crash involving a vehicle hitting a pedestrian and then crossing over a median is categorized as a pedestrian crash. Although it is a pedestrian crash, it also resulted in the vehicle crossing over the median. Such crashes were identified by reviewing the illustrative sketches and descriptions in the police reports. This approach is considered to be conservative as it includes analyzing all the crashes where an errant vehicle crossed a raised median at any point during a crash.

Of the 2,436 crashes that occurred at the 18 locations after median conversion through December 2010, 38 (1.6%) resulted in median crossovers. Of these 38, none were fatal crashes, 20 (52.6%) were PDOs and the rest (47.4%) resulted in injury crashes. Table 8 summarizes the statistics about median crossover crashes by crash location and crash severity at four-lane and six-lane facilities. It can be inferred from Table 8 that median crossover crashes at four-lane facilities are slightly more severe compared with similar crashes at six-lane facilities.

**Table 8: Crash Statistics of Median Crossover Crashes**

| | Four-lane Facilities | | Six-lane Facilities | | Total | |
|---|---|---|---|---|---|---|
| | No. of Crashes | Percent of Crashes | No. of Crashes | Percent of Crashes | No. of Crashes | Percent of Crashes |
| **Crash Location** | | | | | | |
| Signalized Intersection | 5 | 36% | 7 | 29% | 12 | 32% |
| Midblock Location | 9 | 64% | 17 | 71% | 26 | 68% |
| **Total** | **14** | **100%** | **24** | **100%** | **38** | **100%** |
| **Crash Severity** | | | | | | |
| PDO | 6 | 43% | 14 | 58% | 20 | 53% |
| Injury | 8 | 57% | 10 | 42% | 18 | 47% |
| Fatal | 0 | 0% | 0 | 0% | 0 | 0% |
| **Total** | **14** | **100%** | **24** | **100%** | **38** | **100%** |

## CONCLUSIONS AND RECOMMENDATIONS

A before-and-after safety evaluation was conducted at 10 urban arterial sections on Florida's state roads that were converted from TWLTLs to raised medians. Illustrative sketches in police reports were reviewed to flag sites where significant changes were made to roadway characteristics besides constructing raised medians. From these reports, no location was found to have significant changes besides constructing raised medians. However, additional resurfacing, restoration, and rehabilitation improvements that possibly were made at these locations could not be identified from the police reports. As such, the results presented in this study do not take into consideration other cross sectional attributes that might have been improved while the locations were converted from TWLTLs to raised medians.

The before-and-after analysis focused on the shift in crash proportions and changes in crash rates before and after conversion by crash type and crash severity. The Wilcoxon Signed Rank test was performed on the proportion of crashes before and after the construction of raised medians for different crash types and crash severity levels. Overall, a 28.5% reduction in total crash rate was observed after the 10 study locations were converted from TWLTLs to raised medians. The reductions in the proportions of left-turn and right-turn crashes were statistically significant at 89.4% confidence level, while the changes in the proportions of other crash types were not statistically significant. No statistically significant reduction was observed after median construction in the shifts in the proportion of any crash severity type (i.e., PDO crashes, injury crashes, fatal crashes, and fatal and injury crashes). On six-lane arterials, the shifts in proportions of all the crash types and crash severity levels, except left-turn crashes, were found to be statistically insignificant.

The safety performance of four types of median openings was evaluated at four-lane and six-lane facilities. Among the four types of median openings, a uni-directional median opening was found to be the safest alternative for left-turning movements, and a full median opening with left-turn bays in both directions was the least safe alternative for left-turning movements. Among the bi-directional/full median openings, a bi-directional median opening with center island was considered to be the safest alternative for left-turning movements.

In regard to vehicles hitting the curb, of the 2,436 crashes that occurred at the 18 locations after median conversion, only about 2.0% involved vehicles directly hitting the median curb. A majority of these crashes were not severe, therefore, it could be concluded that vehicles hitting the curb is not a serious safety concern. Also, of the 2,436 crashes that occurred after median conversion, 1.6% involved vehicles crossing over the median. Again, a majority of these crashes were not severe. Compared with six-lane facilities, a higher percentage of crashes involving vehicles hitting a raised median on four-lane facilities resulted in injuries (67% on four-lane facilities vs. 41% on

six-lane facilities). In summary, it is concluded that crashes involving vehicles hitting a curb and median crossovers are not a serious safety concern. The crash data did not show evidence that raised medians are an additional hazard compared with TWLTLs.

Although before-and-after safety studies evaluate the safety performance of roadway enhancements by comparing the crash experience before and after the implementation, they are often limited by sample size. Fewer locations often limit the extent of stratification of the study locations. This limitation could be overcome by conducting cross-sectional safety studies with larger sample sizes. In the future, cross-sectional safety studies should be conducted to evaluate the safety benefits of TWLTLs and raised medians. These studies should also analyze locations based on several roadway and geometric features such as land use, number of lanes, and speed limit.

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# Local Sensitivity Analysis of Forecast Uncertainty in a Random-Utility-Based Multiregional Input-Output Model

**by Guangmin Wang and Kara M. Kockelman**

*Transportation systems are critical to regional economies and quality of life. The Random-Utility-Based Multiregional Input-Output Model (RUBMRIO) for trade and travel choices is used here to appreciate the distributed nature of commodity flow patterns across the United States' 3,109 contiguous counties and 12 industry sectors, for rail and truck operations. This paper demonstrates the model's sensitivity to various inputs using the method of local sensitivity analysis with interactions (LSAI). This work simulates both individual effects as well as interaction effects of model inputs on outputs by providing sensitivity indices of model outputs to variations of inputs under two scenarios. Model outputs include predictions of domestic and export trade flows, value of goods produced, labor expenditures, and household and industry consumption levels across the counties in the United States. The LSAI technique allows transportation system operators to appreciate the roles of any model input and the associated uncertainty of outputs.*

## INTRODUCTION

Transportation systems are critical to regional economies and planning. Their spatial structures and cost implications dramatically affect household and firm location choices, production levels, and trade patterns in multiple ways. These choices manifest themselves in various forms of travel demand, impacting the operational performance of the transportation system. To recognize this critical interaction and enhance planning, policy, and investment decisions, integrated models of transportation and land use have been pursued.

Traditional Input-Output (IO) models are popular for simulating expenditure linkages between industries, and between producers and consumers (Leontief and Strout 1963). These models are demand driven in the sense that production levels adjust to meet both final and intermediate demands. Spatial (or interregional, inter-zonal) IO (SIO) analysis extends the classical IO model to include spatial disaggregation when coupled with random utility theory for the distribution of productive input, such as MEPLAN (Hunt and Simmonds 1993; Abraham and Hunt 1999; Rodier et al. 2002; Clay and Johnston 2006), TRANUS (De la Barra et al. 1984; De la Barra 2005; Modelistica 2007; Lefevre 2009), and PECAS (Hunt and Abraham 2003). These models can be made dynamic, by allowing the travel costs associated with freight and people (labor and customer) flows to affect location and land use decisions in the model's next iteration, along with network system changes (e.g., roadway expansions) and exogenous economic shocks (e.g. increases in export demands). Entropy concepts were then proposed, to establish a connection between SIO models, entropy-maximizing theory, and random-utility theory (Wilson 1970; Anas 1984).

Isard (1960) first proposed the extension of the IO model to multiple regions; therefore, it may be referred to as Random-Utility-Based Multiregional Input-Output (RUBMRIO) models. These combine traditional SIO models with a multinomial logit (MNL) model for trade and travel choices to represent the distributed nature of commodity flow patterns. De la Barra (2005) suggested the standard algorithm for the RUBMRIO model, which is usually solved by iteratively applying a set of equations. Each equation describes a key model variable.

Kockelman et al. (2005) developed a RUBMRIO model of Texas trade. Their RUBMRIO model described the production and trade patterns of 18 socio-economic sectors (including

households and government) across Texas' 254 counties. Production and trade typically are driven by export demands at 31 key ports, while specific trade patterns respond to prices, measured in utility units and based on expected minimum transportation costs (represented by distance on a two-mode highway/railway network). Their applications considered network and corridor congestion and the multiplier effects of shifts in demand, by port and sector. Ruiz-Juri and Kockelman (2004) extended the RUBMRIO model to recognize land use constraints on production (and residence), to incorporate domestic demands by other U.S. states, estimate vehicle trips resulting from monetary trades, and capture the effects of the network congestion on trade and production decisions. Based on the above work, Huang and Kockelman (2008) extended the RUBMRIO model to characterize near-term production and trade patterns based on current settlement and earnings patterns, and to introduce dynamic features, which forecast the evolution of a region's trade patterns – from a state of short-term disequilibrium to longer-run scenarios. Du and Kockelman (2012) extended work by Kockelman et al. (2005) to a U.S.-level RUBMRIO model for trade patterns among the nation's 3,109 contiguous counties (excluding Hawaii and Alaska), across 20 socio-economic sectors, and two transportation modes. The applications anticipated trade and location choices resulting from a variety of scenarios, including changes in export demands and transport cost. A series of scenarios were carried out by changing the export demands in each of the 12 export-related sectors to forecast the effects of different export demands on the U.S. economy. Highway congestion effects and transport cost effects on U.S. trade and production patterns were illustrated by a rise or fall in IH40 travel times and the marginal average cost of trucking.

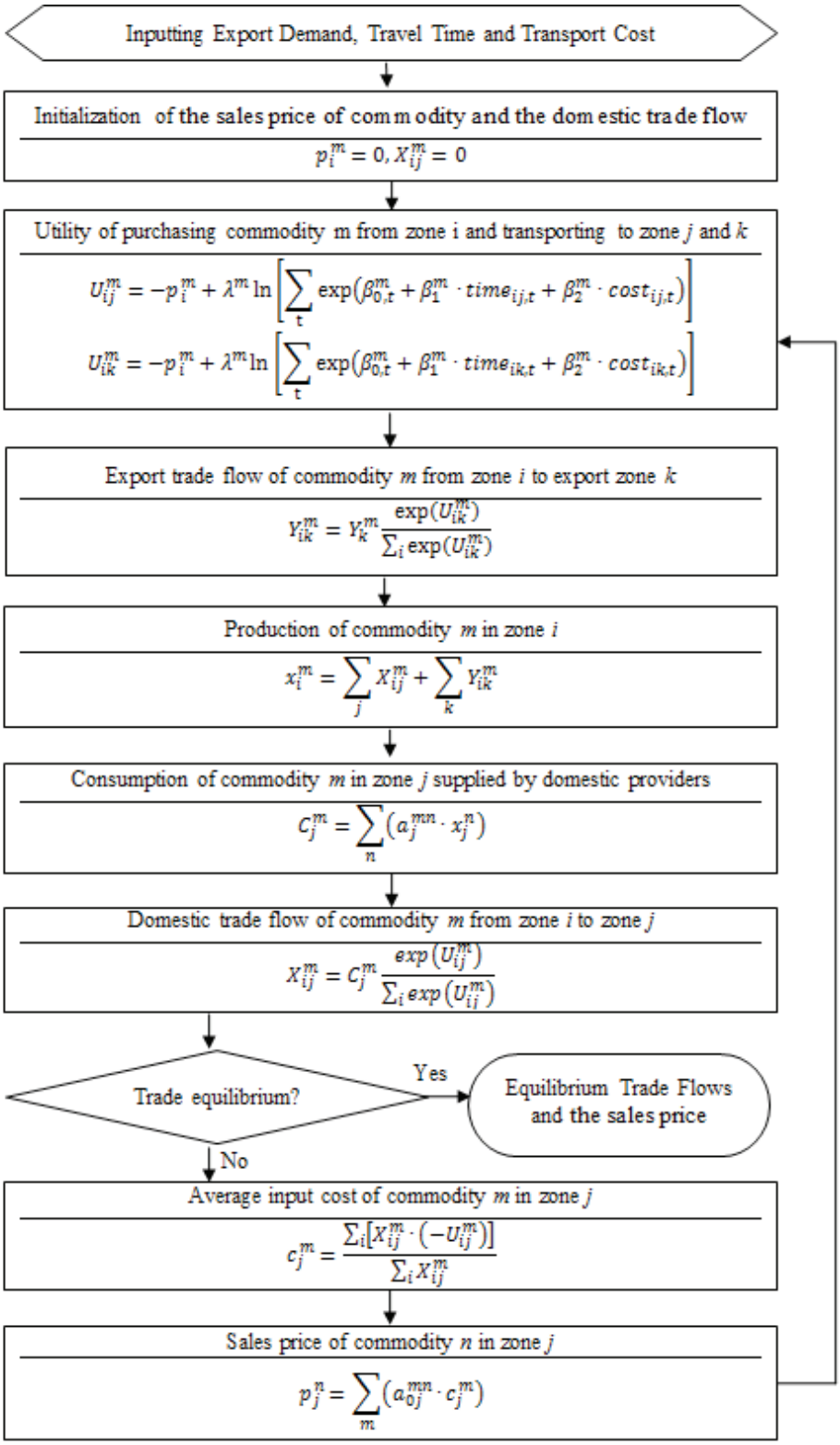
In these studies, they mainly focused on how the effects of inputs (e.g., export demands of different commodities, the transport cost, and network congestion) and parameters (e.g., technical coefficient) on outputs, such as the distribution of trade flows and production. Additionally, they only demonstrated the individual effect of every input on the outputs. In fact, the interaction effects across inputs may amplify or dampen individual effects of inputs on outputs in complex and dynamic urban systems.

Thus, we used the local sensitivity analysis with interaction (LSAI) to evaluate the RUBMRIO model by producing finite change sensitivity indices for the variation of inputs under different scenarios. This feature is particularly appealing when the set of uncertain variables is especially large since this procedure requires a relatively low number of model runs. This paper illustrates how the local sensitivity analysis applies to the case of scenarios in transport and land use models through an analysis of the RUBMRIO model, which simulates not only the individual effect of each input but also all inputs' interaction effects. In this study, a RUBMRIO model is developed for trade patterns among the 3,109 contiguous counties from the continental U.S. across 12 socio-economic sectors and two transportation modes (truck and rail). The following two scenarios are used: simultaneously increasing all foreign export demands (ED), transport costs (TC), and travel times (TT) between counties (or from counties to export zones) by 20% as Scenario 1, and simultaneously decreasing all ED, TC, and TT by 20% as Scenario 2. Applications of the model anticipate changes (including individual effects and interaction effects) of domestic trade flow, export trade flow, production (sum of domestic and export trade flows), and consumption in the continental U.S. resulting from two scenarios. Thus, these scenarios include increasing or decreasing ED, TC, and TT between counties (or from counties to export zones) by 20% in order to forecast their effects on key metrics of the U.S. economy (including production, consumption, and domestic trade flows in continental U.S. States).

## BRIEF INTRODUCTION TO THE RUBMRIO MODEL

RUBMRIO is a transportation-economic model that simulates the flow of goods, labor, and vehicles across a multiregional area (see Figure 1, and Du and Kockelman [2012]). RUBMRIO simulates trade across zones of a region, as motivated by foreign and domestic ED, and computes this trade within numerous economic sectors. IO relationships/tables are used to anticipate consumption needs of commodity producers, and multinomial logit models distribute commodity flows across origin zones and shipment modes.

**Figure 1: RUBMRIO Structure and Solution Algorithm**



**The Utility of Trade Choices**

The application of the random utility theory for cost minimization, domestic trade flows (among counties, as zones) and export flows (from counties to export zones) is based on the utility of purchasing commodity *m* from zone *j* and transporting it via different transportation modes (export it to zone *k*). The utility function is composed of two items, including the price of the commodity, as well as travel time and cost attributes between zones (rather than distance), as shown in Equations (1) and (2).

(1) $U_{ij}^{m} = -p_i^m + \lambda^m \ln[\sum_t \exp(\beta_{0,t}^m + \beta_{1,t}^m time_{ij,t} + \beta_{2,t}^m \cos t_{ij,t})]$

(2) $U_{ik}^{m} = -p_i^m + \lambda^m \ln[\sum_t \exp(\beta_{0,t}^m + \beta_{1,t}^m time_{ik,t} + \beta_{2,t}^m \cos t_{ik,t})]$

$p_i^m$ is the sales price of commodity *m* in county/zone *i*, $time_{ij,t}$ and $cost_{ij,t}$ represent the travel times and costs between zones *i* and *j* via mode *t*. Parameters $\beta_{0,t}^m$, $\beta_{1,t}^m$, and $\beta_{2,t}^m$ were estimated using a series of industry-specific nested logit specifications as described by Ben-Akiva and Lerman (1985).

**Production Function**

Sales price is a key factor influencing consumption of a commodity, purchase choices, production costs, and thus, trade patterns. In the RUBMRIO model, sales price (the cost of producing one unit of commodity *n* in zone *j*) depends on the costs of purchasing raw materials, labor, and necessary services from other producers, including transport costs associated with the shipment of those inputs. The ultimate sales price of commodity by industry *n* from zone *j* is as follows:

(3) $p_j^n = \sum_m a_{0j}^{mn} \times c_j^m$

where $a_{0j}^{mn}$ is the technical coefficient for producing commodity *n* in zone *j*. $a_{0j}^{mn}$ means the dollar values of commodity *m* required to produce one unit of commodity *n* in zone *j*. Thus, they are all dimensionless because their units are in terms of dollar-per-dollar.

They can be calculated through a transactions table (input-output matrix of dollar flows between industries) by dividing each m, n cell's transaction by its corresponding column totally from the original IMPLAN transactions tables (Minnesota IMPLAN Group 1997) for total purchases, both local and imported.

The input costs $c_j^m$, shown in Equation (4), are a flow-weighted average of purchase price for commodity m in zone j and transport costs for commodity m from zone i to zone j (in units of disutility). The weights are domestic trade flows, $X_{ij}^m$.

(4) $c_j^m = \dfrac{\sum_i [X_{ij}^m \cdot (-U_{ij}^m)]}{\sum_i X_{ij}^m}$

**Trade Flows**

Domestic and export trade flows are calculated under an assumption of utility-maximizing/cost-minimizing behavior, which means consumers will choose producer(s) that can supply the lowest cost (including both the price and the transport cost) in order to maximize their utility and (or) minimize their costs. The unobserved heterogeneity of this choice, across producers and consumers, introduces the random elements, which leads to a nested logit model for origin and mode choices. The domestic trade flow, $X_{ij}^m$, and export trade flow, $Y_{ik}^m$, are computed using Equations (5) and (6):

(5) $$X_{ij}^{m} = C_{j}^{m} \frac{\exp(U_{ij}^{m})}{\sum_{i} \exp(U_{ij}^{m})}$$

(6) $$Y_{ik}^{m} = Y_{k}^{m} \frac{\exp(U_{ik}^{m})}{\sum_{i} \exp(U_{ik}^{m})}$$

where $Y_k^m$ is the demand of export zone $k$ for commodity $m$, and $c_j^m$ is the total (dollar) amount of commodity $m$ consumed in zone $j$, which can be obtained as follows:

(7) $$C_{j}^{m} = \sum_{n} a_{j}^{mn} x_{j}^{n}$$

Here, $a_j^{mn}$ represents "local-purchase" technical coefficient for commodity $m$ in zone $j$. Regional purchase coefficients (RPCs) bridge these two styles of technical coefficient matrices by representing the proportion of total demand for a commodity that is supplied by producers within the study area, rather than imported from abroad (MIG 2011). This relationship between $a_{0j}^{mn}$ and $a_j^{mn}$ is shown in Equation (8). Finally, $x_i^m$ is the total production of commodity $m$ in zone $i$, which is the sum of domestic and export flows "leaving" zone $i$, as shown in Equation (9).

(8) $$a_{j}^{mn} = \frac{a_{0j}^{mn} \times RPC^{n}}{\sum_{m} a_{0j}^{mn}}$$

(9) $$x_{i}^{m} = \sum_{j} X_{ij}^{m} + \sum_{k} Y_{ik}^{m}$$

Equations (1) through (9) constitute the majority of the RUBMRIO model, and they are solved iteratively to achieve an equilibrium trade pattern, as described by Zhao and Kockelman (2004), who examined the existence and uniqueness of the equilibrium solution. After inputting foreign export demand, highway distances and railway distances between zones, highway distances and railway distances to export, and transport cost between zones and to export, the iteration procedure begins with initial sales prices and the domestic trade flow at zero. The relative utilities of both domestic and export origin and mode choices are computed. Then, export demands are distributed among production zones to export according to the relative utilities. These export flows give rise to domestic demands and trade flows between counties on the basis of relative utilities. The total productions in zone $i$ are multiplied by corresponding technical coefficients (following import/leakage considerations) in order to estimate the total consumption (set of inputs) required for purchase from domestic counties $j$ (including zone $i$ itself). Average input costs are computed as a flow-weighted average of utilities, and coupled with original technical coefficients to provide updated sales prices, which provide feedback for recalculating of all purchase utilities. This process leads to new iterations, until consecutive trade flows stabilize, achieving system equilibrium.

## LOCAL SENSITIVITY ANALYSIS WITH INTERACTION (LSAI)

While building and using numerical simulation models, sensitivity analysis is an invaluable tool to study how uncertainty in the output of a mathematical model or system is apportioned to different sources of uncertainty in its inputs (Saltelli et al. 2008). Local sensitivity analysis is the assessment of the local impact of input factors' variation on model response by concentrating on the sensitivity in the vicinity of a set of input factors. Such sensitivity is often evaluated through gradients or partial derivatives of the output functions at these input factors, thus other inputs are held constant when studying the local sensitivity of a specific input. Such approaches have been used in evaluating large environmental systems, including climate modeling, oceanography, and hydrology (Cacuci 2003, Castaings et al. 2007). Borgonovo et al. (2014) used Gravity-based Land Use Model (G-LUM) by

Kockelman et al. (2008) to illustrate LSAI techniques and found that the outputs respond almost additively to variations in the model inputs over the given scenarios. Changes in the base year employment assumptions strongly influence future job and land use pattern predictions.

Here, the following mathematical model is used to denote the input-output mapping:

$$(10)\quad y = f(\mathbf{x}), f: \Omega_{\mathbf{x}} \rightarrow \mathbb{R}$$

where $y$ is the output, $\mathbf{x} = (x_1, x_2, \cdots, x_l) \in \Omega_{\mathbf{X}} \subseteq \mathbb{R}^l$ is the vector of the inputs. $l$ is the number of (groups of) inputs. Therefore, $y^0 = f(\mathbf{x}^0)$ the base-case output of the simulation can be obtained by the simulation with inputs to a base-case scenario, $\mathbf{x}^0$. Furthermore, the analyst can know the response of the inputs in each scenario by obtaining different outputs $y^s = f(\mathbf{x}^s)(s = 1,2,\cdots,S)$ (through simulating the alternative scenarios. However, he/she has no information about the sources of change (Borgonovo et al. 2014). The analyst also cannot distinguish both the importance of each input and their individual and interaction effects on the output. Recent works have addressed those problems through the concept of sensitivity analysis setting (Borgonovo et al. 2014).

To identify the relative importance of changes in single input or of interactions between inputs, we can use the following complete decomposition of any finite change in $f(\mathbf{x})$ (Saltelli and Tarantola 2002; Saltelli et al. 2004; Borgonovo et al. 2014):

$$(11)\quad \Delta y = f(\mathbf{x}^1) - f(\mathbf{x}^0) = \sum_{k_1=1}^{l} \Delta_{k_1} f + \sum_{k_1<k_2}^{l} \Delta_{k_1,k_2} f + \cdots + \Delta_{1,2,\cdots,l} f$$

with

$$(12)\quad \begin{cases} \Delta_{k_1} f = f\left(x_{k_1}^1, \mathbf{x}_{\sim k_1}^0\right) - f(\mathbf{x}^0) \\ \Delta_{k_1,k_2} f = f\left(x_{k_1}^1, x_{k_2}^1, \mathbf{x}_{\sim(k_1,k_2)}^0\right) - \Delta_{k_1} f - \Delta_{k_2} f - f(\mathbf{x}^0) \end{cases}$$

and where $\left(x_{k_1}^1, \mathbf{x}_{\sim k_1}^0\right)$ denotes that the th element of the $\mathbf{x}$ vector, is set at the value it assumes in Scenario 1, while all other variables are at their Scenario 0 values. Thus, the change induced by the change of the inputs can be decomposed into individual effects and interaction effects of inputs. Based on such decomposition, finite-change sensitivity indices can be computed as follows:

$$(13)\quad \varphi_{k_1,k_2,\cdots,k_r}^r = \Delta_{k_1,k_2,\cdots,k_r} f$$

where $k_1, k_2, \cdots, k_r$ denotes a group of $r$ indices ($r \leq l$) and $\varphi_{k_1,k_2,\cdots,k_r}^r$ is the portion of due to the interaction of inputs corresponding to the selected indices.

Particularly, the first-order finite-change sensitivity indices are $\varphi_{k_i}^1 = \Delta_i f\,(k_i = 1,2,\cdots,l)$ and the total-order indices of $x_{k_i}$ are $\varphi_{k_i}^T = \Delta_{k_i} f + \sum_{k_i<k_2}^{l} \Delta_{k_i,k_2} f + \cdots + \Delta_{1,2,\cdots,l} f$, where $\varphi_{k_i}^T$ is the total contribution of $x_{k_i}$ to $\Delta y$, and is the sum of the individual contribution of $x_{k_i}$, plus all the contributions due to the interaction of $x_{k_i}$ with the remaining inputs. Thus, the index $\varphi_{k_i}^I = \varphi_{k_i}^T - \varphi_{k_i}^1$ represents the interaction effects associated with $x_{k_i}$ (Borgonovo et al. 2014).

As discussed in the literature (Saltelli and Tarantola 2002; Saltelli et al. 2004), the sign of the first-order indices ($\varphi_{k_i}^I$) is the sign change in y due to the individual change in $x_{k_i}$. The sign of $\varphi_{k_1,k_2,\cdots,k_r}^r$ is the sign of the interaction effects between the inputs $x_{k1}$, $x_{k2}$, and $x_{k3}$. The total-order indices ($\varphi_{k_i}^T$) are the appropriate sensitivity measures, since they deliver not only the individual importance of the inputs, but also account for interaction effects. The magnitudes of $\varphi_{k_1,k_2,\cdots,k_r}^r$ provide the natural sensitivity measures.

## SENSITIVITY ANALYSIS OF THE RUBMRIO MODEL

In this section, the RUBMRIO model is used to anticipate changes of domestic trade flow, export trade flow, production, and consumption in the continental U.S. resulting from two scenarios:

simultaneously increasing and decreasing ED, TC, and TT by 20%. First, the data acquisition and parameters estimates are introduced. Then, the two scenarios are considered through analyzing sensitivity indices and total-order indices. In this sensitivity analysis, one can obtain both individual effects of each input and their interactions' effects. This reflects whether interaction effects across inputs amplify or dampen individual effects.

## DATA ACQUISITION

The primary data source is the U.S. Department of Transportation's Freight Analysis Framework version 3 ($FAF^3$) database of networks and flows between FAF regions (FAF 2007). FAF integrates data from a variety of sources to create a comprehensive picture of freight movement among states and major metropolitan areas by all modes of transport. With data from the U.S. 2007 Commodity Flow Survey and other sources, $FAF^3$ provides estimates for tonnage and value by commodity type, mode, origin, and destination for year 2007 flows. $FAF^3$'s origin-destination-commodity-mode (ODCM) annual freight flows matrix was used to estimate RUBMRIO's nested logit model's origin and mode choice parameters, to calculate all export demands (by port and industry), and evaluate RUBMRIO model predictions. Commodities are classified at the 2-digit level of the Standard Classification of Transported Goods (SCTG) http://www.statcan.gc.ca/eng/subjects/standard/sctg/sctgclass, and were aggregated to the closest 12 economic sectors, according to the codes with a complete description of these categories and their constituent parts shown in Table 1 with corresponding IMPLAN Code and NAICS Code.

**Table 1: Description of Economic Sectors in RUBMRIO Model**

| Sector | Description | SCTG Code | IMPLAN Code | NAICS Code |
|---|---|---|---|---|
| 1 | Agriculture, Forestry, Fishing and Hunting | 1 | 1~19 | 11 |
| 2 | Food, Beverage and Tobacco Product Manufacturing | 2~9 | 41~74 | 311, 312 |
| 3 | Mining | 10~15 | 20~30 | 21 |
| 4 | Petroleum and Coal Product Manufacturing | 16~19 | 115~119 | 324 |
| 5 | Chemicals, Plastics and Rubber Product Manufacturing | 20~24 | 120~152 | 325, 326 |
| 6 | Other Durable & Non-Durable Manufacturing | 25~31, 39 | 75~114, 153~169, 295~304 | 313~316, 321~323, 327, 337 |
| 7 | Primary Metal Manufacturing | 32 | 170~180 | 331 |
| 8 | Fabricated Metal Manufacturing | 33 | 181~202 | 332 |
| 9 | Machinery Manufacturing | 34 | 203~233 | 333 |
| 10 | Computer, Electronic Product and Electrical Equipment Manufacturing | 35, 38 | 234~275 | 334, 335 |
| 11 | Transportation Equipment Manufacturing | 36, 37 | 276~294 | 336 |
| 12 | Miscellaneous Manufacturing | 40, 41, 43 | 305~318 | 339 |

$FAF^3$ flows are also broken down by eight modes of transportation including truck, rail, water, air, multiple modes and mail, pipeline, other and unknown, no domestic mode. See http://faf.ornl.gov/fafweb/Data/FAF3ODCMOverview.pdf for more details about these mode and commodity classes. Considering that truck and rail modes carry 40.1% and 40.2%, respectively, of the U.S.'s 3,344

billion ton-miles of traded commodities according to the 2007 Commodity Flow Survey (http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/commodity_flow_survey/final_tables_december_2009/html/table_01b.html), the RUBMRIO model used here includes just two modes - truck and rail. All other modes are excluded. Travel times and costs between counties (and from counties to export zones) were computed for the county-to-county matrix based on shortest-path distances over TransCAD's highway and railway network models. See https://www.census.gov/geo/reference/codes/cou.html for details about the 3,109 counties from the continental U.S.

**Estimation of Parameters**

As introduced in Equations (1) and (2), parameters $\lambda^m$, and $\beta^m$ reflect producers' and shippers' attraction to an origin zone's size and sensitivity to travel times and costs of the two alternative modes (highway and railway) for each commodity *m*. To estimate such parameters for the nested logit model structure (with lower level for mode choice and upper level for origin choice), FAF[3]'s dollar values of freight flows between 120 domestic zones were used for the 12 economic sectors (as shown in Table 1). Each FAF record was used as a data point or "observation," and its dollar value used as the "weight" factor in the logit's log-likelihood function. In the lower layer of the nested logit model, mode choices were first estimated for each of the 12 sectors. Travel times and costs between counties (and from counties to export zones) are computed based on shortest-path distances over TransCAD's highway and railway networks. For sector *m*, the probability of choosing transport mode *t* between origin *i* and destination *j* is as follows:

$$(14) \quad P_{t|\mathrm{ij}}^{mn} = \frac{\exp(V_{ij,t}^{m})}{\sum_{s} \exp(V_{ij,s}^{m})}$$

where $V_{ij,t}^{m}$, the systematic (non-random) conditional indirect utility, is given by:

$$(15) \quad V_{ij,t}^{m} = \beta_{0,t}^{m} + \beta_{1,t}^{m} time_{ij,t} + \beta_{2,t}^{m} \cos t_{ij,t}$$

$\beta's$ are mode choice parameters to be estimated. ($\beta_{0,railway}$ was set to zero in order to permit statistical identification of the other parameters.)

In the upper layer, the probability of a producer in zone *i* choosing commodity *m* from firms in zone *j* is:

$$(16) \quad P_{ij}^{mn} = \frac{\exp(V_{ij}^{m})}{\sum_{i} \exp(V_{ij}^{m})}$$

where $V_{ij}^{m}$ is the expected maximum utility across mode alternatives plus the origin-size attractiveness term, shown as follows:

$$(17) \quad V_{ij}^{m} = \lambda^{m} \ln[\textstyle\sum_{t} \exp(V_{ij,t}^{m})]$$

Table 2 shows all parameter estimates for the origin and mode choice models by sector (Du and Kockelman 2012).The correlated nature of cost and time variables, and use of assumed (rather than actual) results, is presumably causing the negative coefficient estimates for several sectors. Such situations appear more common for high-weight, low-time-value goods, with long-distance transport relying on rail, rather than the faster mode of trucking.

**Table 2: Estimated Parameters for Nested Logit Models of Origin and Mode Choice**

| Sector | Origin Choice Parameters | | Mode Choice Parameters | | | |
|---|---|---|---|---|---|---|
| | $\lambda^m$ | $\rho^2$ (Rho-Square) | $\beta^m_{0,tuck}$ | $\beta^m_{1,t}$ | $\beta^m_{2,t}$ | $\rho^2$ (Rho-Square) |
| 1 | 0.448 | 0.403 | 5.640 | -4.010 | -4.040 | 0.999 |
| 2 | -1.430 | 0.242 | 5.600 | 1.810 | 0.464 | 0.772 |
| 3 | -3.830 | 0.262 | 1.850 | 0.857 | 0.0761 | 0.109 |
| 4 | 1.010 | 0.493 | 1.670 | -1.560 | -3.410 | 0.755 |
| 5 | 0.801 | 0.206 | 1.420 | -1.010 | -1.120 | 0.486 |
| 6 | 1.090 | 0.081 | 5.540 | 1.540 | 0.575 | 0.562 |
| 7 | 1.690 | 0.130 | 1.430 | -0.823 | -1.280 | 0.817 |
| 8 | 0.173 | 0.16 | 3.180 | -0.478 | -0.741 | 0.936 |
| 9 | 0.339 | 0.224 | -3.610 | -8.500 | -6.980 | 0.934 |
| 10 | 0.097 | 0.288 | -1.590 | -6.000 | -4.160 | 0.613 |
| 11 | -0.840 | 0.130 | -3.470 | -6.090 | -5.270 | 0.825 |
| 12 | 0.805 | 0.272 | 2.830 | -1.900 | -1.960 | 0.926 |

Technical coefficients $\alpha^{mn}$ reflect production technology within counties and are very important parameters in the RUBMRIO model. In this study, the technical coefficients are assumed to be stable due to only considering the situation in the short run. Therefore, they are exogenous to the model, based on IMPLAN's transaction tables derived from U.S. inter-industry accounts and estimate the values of purchases at finer levels of resolution. RPCs describe the proportion of local demand for a commodity that is purchased from local producers. Here, a constant RPC value was used in all counties. These RPCs are generated by IMPLAN automatically, using a set of econometric equations (MIG 2001).

**Sensitivity Analysis of RUBMRIOModel viaTwo Senarios**

This section describes the scenario decomposition applied to RUBMRIO. The 3,109 counties come from the continental U.S. states, as shown in Table 3.

RUBMRIO's three major inputs are as follows:

a) Foreign Export Demand (ED): the foreign export flows via 106 export zones, across 12 economic sectors. ED is assumed to be the only source of final demand, which must be satisfied by the U.S. counties.
b) Transport Costs (TC): travel costs between each pair of counties (or from counties to export zones). We vary travel costs between each pair of counties.TC is the key component of most any trade model, and can rise or fall relatively quickly in response to changing energy prices, labor costs, shipping regulations, and interest rates (which affect the real price of vehicle capital).
c) Travel Times (TT): the travel time between each pair of counties (or from counties to export zones). As a key component of the utility functions, transport time affects trade flow patterns, local production, and consumption.

**Table 3: Continental U.S. States and Counties**

| No. | State | Abbr. | # Counties | No. | State | Abbr. | # Counties |
|---|---|---|---|---|---|---|---|
| 1 | Alabama | AL | 67 | 26 | Nebraska | NE | 93 |
| 2 | Arizona | AZ | 15 | 27 | Nevada | NV | 17 |
| 3 | Arkansas | AR | 75 | 28 | New Hampshire | NH | 10 |
| 4 | California | CA | 58 | 29 | New Jersey | NJ | 21 |
| 5 | Colorado | CO | 64 | 30 | New Mexico | NM | 33 |
| 6 | Connecticut | CT | 8 | 31 | New York | NY | 62 |
| 7 | Delaware | DE | 3 | 32 | North Carolina | NC | 100 |
| 8 | District of Columbia | DC | 1 | 33 | North Dakota | ND | 53 |
| 9 | Florida | FL | 67 | 34 | Ohio | OH | 88 |
| 10 | Georgia | GA | 159 | 35 | Oklahoma | OK | 77 |
| 11 | Idaho | ID | 44 | 36 | Oregon | OR | 36 |
| 12 | Illinois | IL | 102 | 37 | Pennsylvania | PA | 67 |
| 13 | Indiana | IN | 92 | 38 | Rhode Island | RI | 5 |
| 14 | Iowa | IA | 99 | 39 | South Carolina | SC | 46 |
| 15 | Kansas | KS | 105 | 40 | South Dakota | SD | 66 |
| 16 | Kentucky | KY | 120 | 41 | Tennessee | TN | 95 |
| 17 | Louisiana | LA | 64 | 42 | Texas | TX | 254 |
| 18 | Maine | ME | 14 | 43 | Utah | UT | 29 |
| 19 | Maryland | MD | 26 | 44 | Vermont | VT | 14 |
| 20 | Massachusetts | MA | 14 | 45 | Virginia | VA | 134 |
| 21 | Michigan | MI | 83 | 46 | Washington | WA | 39 |
| 22 | Minnesota | MN | 87 | 47 | West Virginia | WV | 55 |
| 23 | Mississippi | MS | 82 | 48 | Wisconsin | WI | 72 |
| 24 | Missouri | MO | 115 | 49 | Wyoming | WY | 23 |
| 25 | Montana | MT | 56 | Total No. of counties | | | 3109 |

The base case scenario used here, $x^0 = (ED^0, TC^0, TT^0)$, is based on data used in Du and Kockelman (2012). The RUBMRIO model is used to examine the different scenarios' effects on the distributions of trade flows and production by simulating those alternative scenarios, after first changing ED in each of the 12 export-related sectors, changing Interstate Highway (IH) 40's TT by 10%, and changing the marginal average time of trucking by 20% up and then down, each factor one at a time (Du and Kockelman 2012). In this paper, one can consider the two distinctive scenarios $x^1 = (ED^1, TC^1, TT^1)$ (simultaneously increasing ED, TC, and TT by 20%) and $x^2 = (ED^2, TC^2, TT^2)$ (simultaneously decreasing ED, TC, and TT by 20%). Therefore, the change of each model output resulted from $x^0$ to $x^1$ (or $x^2$) can be decomposed into eight terms, which account for the individual effect in ED, TC, and TT, their interaction effects in pairs, and in the residual term that contains their overall and residual interaction. Thus, the following sensitivity indices can be obtained:

$\varphi^1_{ED}, \varphi^1_{TC}, \varphi^1_{TT}, \varphi^2_{ED,TC}, \varphi^2_{ED,TT}, \varphi^2_{TC,TT}, \varphi^3_{ED,TC,TT}$ and total-order indices

$$(18)\quad \begin{cases} \varphi^T_{ED} = \varphi^1_{ED} + \varphi^2_{ED,TC} + \varphi^2_{ED,TT} + \varphi^3_{ED,TC,TT} \\ \varphi^T_{TC} = \varphi^1_{TC} + \varphi^2_{ED,TC} + \varphi^2_{TC,TT} + \varphi^3_{ED,TC,TT} \\ \varphi^T_{TT} = \varphi^1_{TT} + \varphi^2_{ED,TT} + \varphi^2_{TC,TT} + \varphi^3_{ED,TC,TT} \end{cases}$$

Simultaneously increasing (or decreasing) ED, and TC and TT by 20% will have different first-order effects, interaction effects and total-order effects on domestic trade flow (D), export trade flow (E), production (P) and consumption (C) in counties, where production is the sum of D and E. To obtain each state's overall effect estimate, we summed all county-level effects across each continental U.S. state. Hence, we record 20 states with the largest increase and decrease of effects on domestic trade flows in these two scenarios in Tables 4 through 9. This paper records 10 states with largest and smallest changes in domestic trade flows by the first-order and total-order effects of ED, because ED has the same sign with different magnitude of first-order and total-order effects on domestic trade flows, production, and consumption in every state under each scenario. Apart from the first-order and total-order effects of ED, other effects on the domestic trade flows may be negative and positive in different states under each scenario. This paper records 10 states with negative and positive changes (where five states with largest and five states with smallest) in domestic trade flows by the first-order and total-order effects of TC and TT, and interaction effects under each scenario.

**Table 4: Scenario 1's First-order Effects**

| The First-order effects of ED | | | | The First-order effects of TC | | | | The First-order effects of TT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) |
| DC | 165 | 47 | 188 | VA | -114148 | 4350 | -103268 | VA | -96449 | 6419 | -84894 |
| DE | 2720 | 415 | 2796 | KY | -56319 | -2178 | -54369 | KY | -34360 | -638 | -31778 |
| RI | 6491 | 1085 | 6778 | NC | -55806 | -447 | -54591 | NC | -31924 | 1389 | -28722 |
| NH | 10622 | 958 | 10679 | GA | -50009 | -1578 | -48141 | GA | -29637 | 132 | -28313 |
| MA | 15350 | 1922 | 15627 | KS | -47976 | -2208 | -45821 | FL | -4224 | 443 | -3873 |
| ME | 17331 | 2197 | 17645 | WI | -2548 | -144 | -3194 | RI | -1579 | 3 | -1378 |
| NV | 18431 | 1639 | 18535 | VT | -1886 | -48 | -1810 | DE | -1448 | -2 | -1319 |
| CT | 22510 | 3730 | 23124 | RI | -1822 | 55 | -1688 | ME | -1232 | 129 | -1237 |
| OR | 25721 | 3222 | 26286 | DE | -1444 | 8 | -1363 | MD | -980 | 272 | -1017 |
| VT | 30841 | 4628 | 32302 | DC | -98 | -2 | -94 | DC | -94 | 1 | -84 |
| MI | 172770 | 18397 | 172500 | NH | 3051 | -14 | 2803 | MA | 24 | 185 | 7 |
| AL | 180749 | 11601 | 181083 | NV | 4506 | -106 | 4155 | NM | 897 | 382 | 823 |
| NC | 183067 | 28791 | 188548 | MO | 4830 | -1730 | 539 | NJ | 907 | 539 | 1793 |
| NY | 195666 | 22995 | 199699 | AL | 8081 | 844 | 10089 | MS | 1041 | -396 | 1177 |
| MO | 281036 | 24862 | 272145 | AZ | 8688 | -77 | 8595 | PA | 2064 | 1945 | 2052 |
| CA | 342043 | 9666 | 331227 | AR | 28212 | -616 | 26441 | WY | 48815 | 1073 | 46891 |
| NE | 350462 | 9918 | 338926 | WY | 43631 | 383 | 42526 | AR | 53090 | 310 | 51705 |
| CO | 356807 | 12362 | 351349 | CO | 103650 | -731 | 108186 | CA | 112864 | -266 | 109555 |
| TX | 385618 | 56409 | 401756 | CA | 112217 | -1837 | 109769 | CO | 174080 | 1289 | 172090 |
| VA | 630612 | 79390 | 646597 | NE | 137043 | -1023 | 137523 | NE | 174540 | 212 | 163210 |

**Note:** Simultaneously increasing all ED, TC and TT by 20% as Scenario 1.

The first-order effects of ED are positive on all of these outputs. That is to say, an increase in ED corresponds to an increase in domestic trade flows, export trade flows, production, and consumption. Table 4 reports the 20 states with the largest and smallest changes in domestic trade flows by the first-order effects of ED. Table 4 shows ED has the strongest first-order effects on VA's domestic trade flows, export trade flows, production, and consumption. Increases in TX's domestic and export trade flows, production, and consumption resulting from a 20% increase in ED are almost half of the increase in VA's, although TX exhibits the second strongest first-order ED effects. At the same time, ED has almost no first-order effects on the small region/district of DC (with predicted changes in domestic trade flows, export trade flows, production, and consumption of just $165, $47, $212, and $188, respectively). Compared with DC, DE (a very small state) exhibits the second weakest ED effects (with values of $2,720, $415, $3,136, and $2,796, respectively).

As opposed to ED, TC and TT have positive or negative effects on domestic and export trade flows, production, and consumption in different states under Scenario 1. Table 4 displays five states with both negative and positive changes in domestic trade flows via TC's and TT's first-order effects. VA suffers the strongest negative effects to its domestic trade flows (falling $114,148) when increasing TC by 20%, but with VA's export trade flows predicted to rise by $4,350 (the most of any shown state). KY, NC, and GA follow VA in decreasing order of domestic trade flow impacts: -$56,319, -$55,806, and -$50,009, respectively. VA, KY, NC, and GA exhibit the strongest negative effects on their production and consumption due to increasing TC by 20%. However, among states with increasing domestic trade flows, NE, CA, and CO exhibit the biggest increase of domestic trade flows, with values of $137,043, $112,217, and $103,650, respectively. TC also has the strongest positive effect on their production and consumption although their export trade flows decrease because of increasing TC. Increasing TC has almost null (positive or negative) effects on export trade flows in DC, DE, NH, and VT because the (negative or positive) changes of their export trade flows are less than $50. TT has the strongest negative effects on VA's domestic trade flows, decreasing by $96,449 compared with $34,360 (the second decreasing of export trade flows in KY) and has the strongest positive effects on export trade flows in VA, increasing by $6,419. VA, KY, NC, and GA have the strongest negative effect on their production and consumption due to increasing TT by 20%. However, when increasing TT by 20%, CO, NE, and CA obtain the biggest increase of domestic trade flows, production, and consumption although CA's export trade flow decreases by $266 because of increasing TT. Increasing TT has almost null (positive or negative) effects on export trade flows in DC, DE, and RI because the (negative or positive) changes of their export trade flows are less than $5.

To sum up, TC or TT have the same sign with different magnitude of first-order effect on domestic trade flows, production and consumption in VA, KY, NC, GA, CO, NE, and CA. ED is the most influential factor on all outputs compared with TC and TT. In some states, increasing TC and TT have completely opposite effects on domestic trade flows, export trade flows, production, and consumption.

The interaction effects for domestic trade flows can be negative or positive across different states. Table 5 shows 10 states with both negative and positive changes (five states with largest and five states with smallest) in domestic trade flows for Scenario 1's interaction effects. Table 5 shows that all four types of interaction effects (ED&TC, ED&TT, TC&TT, ED&TC&TT) are most strongly negative in the case of Virginia's (VA's) domestic trade flows and consumption, with values of $22,830 and -$20,654 (for ED&TC effects on domestic flows and consumption), -$19,290 and -$16,979 (for ED&TT effects), -$106,322 and -$104440 (for TC&TT effects), and -$21,264 and -$20,888 (for ED&TC&TT effects). In other words, VA is estimated to experience the largest losses of domestic trade flows and consumption when ED, TC, and TT are all increased together by 20%. However, ED&TC and ED&TT have the biggest positive interaction effects on VA's export trade flows, with values of $870 and $1,284, while TC&TT and ED&TC&TT are anticipated to have the greatest negative interaction effects (of -$3,633 and -$727, respectively) on VA's export trade flows. Thus, increasing ED and TC, combined with ED and TT, will lead to the biggest increase of VA's export trade flows while increasing TC and TT, combined with ED, TC, and TT will induce

**Table 5: Scenario 1's Interaction Effects**

| ED&TC | | | | ED&TT | | | | TC&TT | | | | ED&TC&TT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) |
| VA | -22830 | 870 | -20654 | VA | -19290 | 1284 | -16979 | VA | -106322 | -3633 | -104440 | VA | -21264 | -727 | -20888 |
| KY | -11264 | -436 | -10874 | KY | -6872 | -128 | -6356 | AL | -47868 | 81 | -47273 | AL | -9574 | 16 | -9455 |
| NC | -11161 | -89 | -10918 | NC | -6385 | 278 | -5744 | KY | -21770 | -355 | -19375 | KY | -4354 | -71 | -3875 |
| GA | -10002 | -316 | -9628 | GA | -5927 | 26 | -5663 | WI | -10872 | -138 | -10178 | WI | -2174 | -28 | -2036 |
| KS | -9595 | -442 | -9164 | IN | -3927 | -95 | -3664 | NC | -10738 | -432 | -10092 | NC | -2148 | -86 | -2018 |
| WI | -510 | -29 | -639 | RI | -316 | 1 | -276 | OR | -672 | 45 | -633 | OR | -134 | 9 | -127 |
| VT | -377 | -10 | -362 | DE | -290 | 0 | -264 | MS | -302 | 55 | -9 | MS | -60 | 11 | -2 |
| RI | -364 | 11 | -338 | ME | -246 | 26 | -247 | DE | -267 | 1 | -220 | DE | -53 | 0 | -44 |
| DE | -289 | 2 | -273 | MD | -196 | 54 | -203 | NH | -47 | 33 | -17 | NH | -9 | 7 | -3 |
| DC | -20 | 0 | -19 | DC | -19 | 0 | -17 | DC | -37 | 7 | -29 | DC | -7 | 1 | -6 |
| NH | 610 | -3 | 561 | MA | 5 | 37 | 1 | WY | 119 | -194 | -27 | WY | 24 | -39 | -5 |
| NV | 901 | -21 | 831 | NM | 179 | 76 | 165 | ME | 138 | 148 | 182 | ME | 28 | 30 | 36 |
| MO | 966 | -346 | 108 | NJ | 181 | 108 | 359 | MD | 310 | 213 | 309 | MD | 62 | 43 | 62 |
| AL | 1616 | 169 | 2018 | MS | 208 | -79 | 235 | FL | 517 | 413 | 563 | FL | 103 | 83 | 113 |
| AZ | 1738 | -15 | 1719 | PA | 413 | 389 | 410 | CT | 584 | 211 | 655 | CT | 117 | 42 | 131 |
| AR | 5642 | -123 | 5288 | WY | 9763 | 215 | 9378 | MO | 19019 | 1085 | 14295 | MO | 3804 | 217 | 2859 |
| WY | 8726 | 77 | 8505 | AR | 10618 | 62 | 10341 | AR | 19688 | 198 | 19001 | AR | 3938 | 40 | 3800 |
| CO | 20730 | -146 | 21637 | CA | 22573 | -53 | 21911 | MT | 20743 | 508 | 23178 | MT | 4149 | 102 | 4636 |
| CA | 22443 | -367 | 21954 | CO | 34816 | 258 | 34418 | TX | 21532 | 3853 | 20955 | TX | 4306 | 771 | 4191 |
| NE | 27409 | -205 | 27505 | NE | 34908 | 42 | 32642 | CO | 24523 | 1303 | 29241 | CO | 4905 | 261 | 5848 |

**Note:** Simultaneously increasing all ED, TC and TT by 20% as Scenario 1.

the biggest decrease of VA's export trade flows. KY, NC, GA, and KS are the next four states that follow VA in terms of domestic trade flow losses and consumption reductions, thanks to the negative interaction effects between ED and TC, as well as interaction effects between ED and TT.

The states of AL, KY, WI, and NC are expected to follow VA in terms of lowered domestic trade flows and consumption due to the negative interaction effects between TC and TT, as well as interaction effects among ED, TC, and TT. VA and AL are expected to experience the greatest negative interaction effects on domestic trade flows, production and consumption, when TC and TT rise together and/or ED, TC, and TT rise together. However, VA's changes in domestic trade flows, production, and consumption more than double those of AL. NE, CA, and CO are estimated to experience the greatest increases in domestic trade flows, including production and consumption values over $20,000, although their export trade flows are expected to fall under interaction effects between ED and TC. The interaction effects between ED and TT also trigger the greatest increases in domestic trade flows, including production and consumption values over $20,000 in NE, CO, and CA. However, CA's export trade flows are nearly unchanged, falling by just $53, while NE's and CO's export trade flows are projected to rise by $42 and $258, because of interaction effects between ED and TT. CO, TX, and MT are predicted to experience the greatest increases in domestic trade flows, as well as production and consumption, and their export trade flows also rise, thanks to interaction effects between ED and TC, and among ED, TC, and TT. Essentially, trade, production and consumption are able to shift in a variety of ways across a set of networked states and regions; so it is valuable to have a model like RUBMRIO to anticipate those movements and techniques like LSAI to appreciate the sources of variations in model outputs.

The negative or positive changes of domestic trade flows in other states are all less than $9,000. Interactions between ED and TC have negligible (under $100) effects on export trade flows in 10 of the above 20 states. Thirteen of the 20 states exhibit negligible export-flow change from interactions effects between ED and TT. Six of the 20 states have negligible changes in export flows when TC and TT interactions are considered, and 15 have negligible export-flow effects from interactions across ED, TC, and TT. Meaningfully, domestic trade flow effects from interactions between TC and TT and among ED, TC, and TT all share the same signs/direction, but with different magnitudes, in each of the 20 states.

Table 6 shows the total-order effects of ED, TC, and TT on domestic and export trade flows and consumption in the 20 continental U.S. states listed. Similar to ED's first-order effects, ED's total-order effects are all positive on these outputs in all states - and ED is expected to have the strongest total-order effect on VA's domestic trade flows, export trade flows, and consumption. However, in VA, ED's total-order effects are less than its first-order effects on domestic trade flows and consumption. TX exhibits the second strongest total-order effects for ED on export trade flows and production (when summing domestic and export trade flows), and ED has its next-strongest total-order effects on domestic trade flow and consumption in CO. DC and DE, as very small regions, exhibit the weakest total-order effects of ED on domestic trade flows, export trade flows, and consumption.

The strongest negative total-order effects of TC on domestic trade flows and consumption happen in VA, although the total-order effects of TC on export trade flows is positive. KY, NC, and GA follow VA in negative total-order effects of TC on domestic trade flows and consumption with negative total-order effects of TC on export trade flows. NE, CO, and CA have the strongest total-order effects of TC on domestic trade flows and consumption while the total-order effects of TC on export trade flows is positive in CO and are negative in CA and NE. TC has almost null (positive or negative) total-order effects on export trade flows in DC, DE, MA, ME, NH, NV, and RI because the (negative or positive) changes of their export trade flows are less than $100. The largest decrease resulted from the total-order effect of TT on the domestic trade flows and consumption also happen in VA, which is the same as the first-order effect of TT. However, AL has the second strongest total-order effects of TT on its domestic trade flows and consumption (-$71,297 and -$70,464, respectively), while its export trade flows increase by $1,140. CO and NE have the strongest positive total-order effects of TT on their domestic trade flows and consumptions

with values over $200,000. The biggest increase of export trade flows happens in TX with $10,611 compared with $3,343, which is the second largest increase of export trade flows in VA. TT has almost null (positive or negative) total-order effects on export trade flows in DC and TN because the (negative or positive) changes of their export trade flows are less than $100.

**Table 6: Scenario 1's Total-order Effects**

| Total-order Effects of ED | | | | Total-order Effects of TC | | | | Total-order Effects of TT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) |
| DC | 119 | 48 | 147 | VA | -264564 | 860 | -249249 | VA | -243325 | 3343 | -227200 |
| DE | 2089 | 417 | 2216 | KY | -93706 | -3039 | -88494 | AL | -71297 | 1140 | -70464 |
| RI | 5665 | 1080 | 6015 | NC | -79852 | -1055 | -77619 | KY | -67356 | -1191 | -61384 |
| NH | 12351 | 981 | 12311 | GA | -61781 | -1355 | -58511 | NC | -51195 | 1148 | -46576 |
| MA | 14767 | 1972 | 15060 | KS | -58686 | -2624 | -55517 | GA | -37334 | 697 | -34718 |
| ME | 16225 | 2222 | 16565 | ME | -5154 | -5 | -4996 | MN | -1980 | 974 | -1592 |
| CT | 20017 | 3858 | 20788 | MA | -3527 | 75 | -3407 | UT | -1373 | 1353 | -308 |
| NV | 21280 | 1642 | 21215 | RI | -3062 | -30 | -2920 | ME | -1313 | 333 | -1265 |
| OR | 24644 | 3160 | 25234 | DE | -2053 | 11 | -1899 | MD | -804 | 581 | -850 |
| MD | 30683 | 3707 | 30929 | DC | -161 | 6 | -147 | DC | -157 | 10 | -136 |
| NC | 163373 | 28893 | 169867 | VT | 64 | 398 | 286 | TN | 179 | -51 | 2922 |
| MI | 169966 | 18289 | 168884 | NJ | 1056 | 401 | -29 | MS | 886 | -410 | 1402 |
| AL | 170482 | 11960 | 171357 | NH | 3605 | 22 | 3343 | PA | 1119 | 2503 | 721 |
| NY | 195670 | 22928 | 200108 | SD | 6316 | -890 | 4729 | OR | 1771 | 181 | 1868 |
| MO | 287785 | 24902 | 279430 | NV | 7340 | -76 | 6855 | MA | 1777 | 357 | 1627 |
| CA | 386015 | 9355 | 374455 | MT | 53423 | -118 | 56128 | TX | 69602 | 10611 | 68913 |
| TX | 388125 | 57750 | 403958 | AR | 57480 | -502 | 54530 | AR | 87333 | 610 | 84848 |
| NE | 414246 | 9848 | 400944 | CA | 128398 | -1547 | 127903 | CA | 129173 | 338 | 127646 |
| CO | 417258 | 12734 | 413252 | CO | 153808 | 687 | 164912 | NE | 218249 | 805 | 207077 |
| VA | 567228 | 80817 | 588077 | NE | 173254 | -677 | 176253 | CO | 238323 | 3111 | 241597 |

**Note:** Simultaneously increasing all ED, TC and TT by 20% as Scenario 1.

As shown in Table 7, the first-order effects of ED are negative on all of these outputs. In other words, a decrease in ED leads to reductions in domestic trade flows, export trade flows, and consumption, as expected. Table 7 reports the 20 states with the largest and smallest changes in domestic trade flows, via ED's first-order effects. Table 4 shows ED's strongest first-order effects are on VA's domestic trade flows, export trade flows, and consumption. TX, CO, NE, and CA follow, with domestic trade flow and consumption losses all below-$300,000 and export trade flows losses below-$9,000.

Different from ED's rather consistently directed effects, TC and TT changes lead to a variety of changes in domestic and export trade flows, production, and consumption across different states, under Scenario 2. ED is the most influential factor, overall, but TC and TT lie directly in the transportation infrastructure and operations domains, so they are of great interest to transportation policymakers and system managers. Table 7 reports five states with both negative and positive changes in domestic trade flows due to TC's and TT's first-order effects. NE is estimated/predicted to exhibit the greatest losses in domestic trade flows and consumption when TC or TT fall (by 20%), yet negligible export trade flow effects (just -$85). CO and CA are next in terms of domestic trade flow and consumption losses, from TC or TT's first-order effects. Consistent with other evaluations, discussed above, TC's and TT show the strongest positive first-order effects on VA's domestic trade

flows and consumption, with TX coming in second for TC's effects and GA coming in second for TT's first-order effects on domestic trade flow and consumption.

**Table 7: Scenario 2's First-order Effects**

| First-order effects of ED | | | | First-order effects of TC | | | | First-order effects of TT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) |
| VA | -630612 | -79390 | -646597 | NE | -193528 | 693 | -190871 | NE | -176883 | -85 | -170565 |
| TX | -385618 | -56409 | -401756 | CO | -156550 | 430 | -159040 | CO | -152806 | -694 | -154252 |
| CO | -356807 | -12362 | -351349 | CA | -149633 | 1495 | -144509 | CA | -109540 | 392 | -107205 |
| NE | -350462 | -9918 | -338926 | MT | -78084 | 124 | -78060 | MO | -63347 | -2138 | -64246 |
| CA | -342043 | -9666 | -331227 | WY | -60586 | -1086 | -59035 | WY | -60095 | -1638 | -58918 |
| MO | -281036 | -24862 | -272145 | WV | -8536 | -752 | -6147 | NY | -6441 | -1330 | -8525 |
| NY | -195666 | -22995 | -199699 | MS | -7775 | 90 | -6173 | NH | -4746 | -105 | -4569 |
| NC | -183067 | -28791 | -188548 | WA | -7460 | -3017 | -9239 | NJ | -4651 | -887 | -4898 |
| AL | -180749 | -11601 | -181083 | NV | -5820 | 14 | -5489 | OR | -2322 | -63 | -2238 |
| MI | -172770 | -18397 | -172500 | NH | -4022 | -66 | -3816 | PA | -337 | -1866 | -476 |
| VT | -30841 | -4628 | -32302 | DC | 109 | -1 | 103 | MA | 47 | -205 | 17 |
| OR | -25721 | -3222 | -26286 | NJ | 480 | -236 | 941 | RI | 58 | -147 | -146 |
| CT | -22510 | -3730 | -23124 | DE | 1257 | -47 | 1179 | DC | 92 | -2 | 84 |
| NV | -18431 | -1639 | -18535 | RI | 1656 | -118 | 1395 | DE | 640 | -78 | 561 |
| ME | -17331 | -2197 | -17645 | VT | 1770 | -78 | 1506 | MD | 1382 | -385 | 1218 |
| MA | -15350 | -1922 | -15627 | NC | 57664 | -1519 | 54104 | ID | 35861 | 1012 | 34357 |
| NH | -10622 | -958 | -10679 | GA | 61866 | 823 | 58839 | TX | 36517 | -1689 | 28745 |
| RI | -6491 | -1085 | -6778 | KY | 64426 | 1406 | 61551 | IN | 36729 | 718 | 34628 |
| DE | -2720 | -415 | -2796 | TX | 69416 | 349 | 63565 | GA | 49358 | -184 | 46525 |
| DC | -165 | -47 | -188 | VA | 83199 | -8727 | 69003 | VA | 71359 | -9414 | 55997 |

**Note:** Simultaneously decreasing all ED, TC and TT by 20% as Scenario 2.

Lower TC is predicted to have negligible effects on export trade flows in DC, DE, MS, NH, NV, and VT, with associated values of -$1, -$47, $90, -$66, $14, and -$78, respectively (all less than $100, in absolute terms). And lower TT values have almost no effect on export trade flows in DC, DE, NE, and OR (with values falling by $2, $78, $85, and $63, respectively) and on domestic trade flows in DC, MA, and RI (with values rising by $92, $47, and $58, respectively).

Domestic trade flow effects for each pair of ED, TC, and TT input assumptions, and across all three sets of inputs, vary in direction across different states. Table 8 records five states with both negative and positive effects, for the largest and smallest changes in domestic trade flows by interaction effects under Scenario 2. Table 8 shows how interaction effects between each pair of ED, TC, and TT input assumptions are greatest for VA's domestic trade flows and consumption (with values falling by $16,640 and $13,801, $14,272 and $11,119, and $46,465 and $42,591, respectively), while NE offers the biggest losses in domestic flows and consumption estimates (with values falling $8,565 and $8,874) as a result of the interaction effects among ED, TC, and TT. However, ED&TC, ED&TT, and TC&TT pairs have the biggest *positive* interaction effects on NE's domestic flows and consumption (with values rising $38,706 and $38,174, $35,377 and $34,113, and $42,823 and $44,372, respectively), while ED&TC&TT has the biggest positive interaction effects on VA's domestic flows and consumption (with impacts of +$9,273 and +$8,518, respectively). TX follows VA in decreasing of domestic trade flows and consumption (with values -$13,883 and -$12,713), while CO follows NE in rising domestic trade flows and consumption (with values of +$31,310

**Table 8: Scenario 2's Interaction Effects**

| ED&TC | | | | ED&TT | | | | TC&TT | | | | ED,TC&TT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) |
| VA | -16640 | 1745 | -13801 | VA | -14272 | 1883 | -11199 | VA | -46365 | 565 | -42591 | NE | -8565 | -102 | -8874 |
| TX | -13883 | -70 | -12713 | GA | -9872 | 37 | -9305 | AL | -32040 | 298 | -31924 | MT | -5771 | -83 | -6029 |
| KY | -12885 | -281 | -12310 | IN | -7346 | -144 | -6926 | KY | -25142 | -260 | -23535 | CO | -5326 | -229 | -5837 |
| GA | -12373 | -165 | -11768 | TX | -7303 | 338 | -5749 | GA | -18567 | 715 | -16914 | MO | -3616 | -120 | -2740 |
| NC | -11533 | 304 | -10821 | ID | -7172 | -202 | -6871 | TX | -17030 | 1001 | -14924 | AR | -3443 | -53 | -3292 |
| VT | -354 | 16 | -301 | MD | -276 | 77 | -244 | MD | -1074 | 167 | -966 | NH | -253 | -7 | -239 |
| RI | -331 | 24 | -279 | DE | -128 | 16 | -112 | RI | -945 | -75 | -876 | VT | -251 | -24 | -246 |
| DE | -251 | 9 | -236 | DC | -18 | 0 | -17 | FL | -677 | 356 | -585 | OR | -143 | -13 | -134 |
| NJ | -96 | 47 | -188 | RI | -12 | 29 | 29 | DE | -56 | 35 | -42 | MA | -35 | -15 | -29 |
| DC | -22 | 0 | -21 | MA | -9 | 41 | -3 | DC | -28 | 4 | -24 | NM | -17 | -61 | -16 |
| NH | 804 | 13 | 763 | PA | 67 | 373 | 95 | NM | 83 | 303 | 79 | DC | 6 | -1 | 5 |
| NV | 1164 | -3 | 1098 | OR | 464 | 13 | 448 | MA | 176 | 77 | 146 | DE | 11 | -7 | 8 |
| WA | 1492 | 603 | 1848 | NJ | 930 | 177 | 980 | OR | 715 | 63 | 671 | FL | 135 | -71 | 117 |
| MS | 1555 | -18 | 1235 | NH | 949 | 21 | 914 | VT | 1256 | 120 | 1228 | RI | 189 | 15 | 175 |
| WV | 1707 | 150 | 1229 | NY | 1288 | 266 | 1705 | NH | 1267 | 35 | 1196 | MD | 215 | -33 | 193 |
| WY | 12117 | 217 | 11807 | WY | 12019 | 328 | 11784 | AR | 17215 | 264 | 16461 | TX | 3406 | -200 | 2985 |
| MT | 15617 | -25 | 15612 | MO | 12669 | 428 | 12849 | MO | 18081 | 598 | 13698 | GA | 3713 | -143 | 3383 |
| CA | 29927 | -299 | 28902 | CA | 21908 | -78 | 21441 | CO | 26629 | 1147 | 29184 | KY | 5028 | 52 | 4707 |
| CO | 31310 | -86 | 31808 | CO | 30561 | 139 | 30850 | MT | 28855 | 414 | 30146 | AL | 6408 | -60 | 6385 |
| NE | 38706 | -139 | 38174 | NE | 35377 | 17 | 34113 | NE | 42823 | 512 | 44372 | VA | 9273 | -113 | 8518 |

**Note:** Simultaneously decreasing all ED, TC and TT by 20% as Scenario 2.

and +$31,808) for interaction effects between ED and TC. However, ED and TC have almost no interaction effects (all less than $100, in magnitude) on TX (-$70), CO (-$86) and nine other states' export trade flows (among the 20 shown here). GA follows VA in decreasing of domestic trade flows and consumption (with values falling by $9,872 and $9,305), while CO follows NE in terms of rising domestic trade flows and consumption (with values of +$30,561 and +$30,850), thanks to interaction effects between ED and TT. However, ED and TT have almost no interaction effects (all less than $100, in magnitude) on GA ($37) and eight other states' export trade flows (among the 20 shown here). AL follows VA in terms of falling domestic trade flows and consumption (with values of -$32,040 and -$31,924), while MT follows NE in increasing of domestic trade flows and consumption (with impacts of +$28,855 and +$30,146), thanks to interaction effects between TC and TT. However, TC and TT have almost no interaction effects (all less than $100, in magnitude) on six other states' export trade flows (among the 20 shown here). MT follows NE in decreasing of domestic trade flows and consumption (with values of -$5,771 and -$6,029), while AL follows VA in terms of rising domestic trade flows and consumption (with values of $6,408 and $6,385), via interaction effects among ED, TC, and TT. However, ED, TC, and TT have almost no interaction effects (all less than $100, in magnitude) on MT (-$83), AL (-$60), and 12 other states' export trade flows (among the 20 shown here).

**Table 9: Scenario 2's Total-order Effects**

| Total-order Effects of ED | | | | Total-order Effects of TC | | | | Total-order Effects of TT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | D($) | E($) | C($) | | D($) | E($) | C($) | | D($) | E($) | C($) |
| VA | -652,250 | -75,875 | -663,079 | NE | -120,564 | 964 | -117,200 | NE | -107,248 | 341 | -100,955 |
| TX | -403,399 | -56,341 | -417,233 | CA | -115,156 | 1,711 | -110,605 | CO | -100,942 | 362 | -100,054 |
| CO | -300,261 | -12,538 | -294,527 | CO | -103,937 | 1,261 | -103,885 | CA | -83,082 | 830 | -80,762 |
| CA | -291,346 | -10,172 | -282,135 | AL | -43,095 | -532 | -43,583 | WY | -39,460 | -1,292 | -38,744 |
| NE | -284,945 | -10,142 | -275,514 | WY | -39,853 | -851 | -38,837 | MO | -36,213 | -1,232 | -40,438 |
| MO | -261,872 | -24,429 | -253,519 | AZ | -12,022 | 48 | -11,594 | OR | -1,285 | 0 | -1,254 |
| NY | -197,639 | -22,987 | -200,875 | WV | -8,795 | -696 | -7,793 | OH | -1,246 | -616 | -2,121 |
| NC | -197,554 | -28,075 | -201,763 | WA | -8,395 | -2,117 | -9,444 | RI | -710 | -178 | -817 |
| MI | -168,017 | -18,166 | -168,415 | NV | -3,600 | 41 | -3,386 | SD | -536 | -127 | -1,047 |
| AL | -167,425 | -11,148 | -167,334 | NH | -2,204 | -24 | -2,096 | SC | -503 | -286 | -794 |
| AZ | -28,613 | -1,110 | -27,859 | DC | 65 | 3 | 64 | DC | 52 | 2 | 48 |
| OR | -26,502 | -3,281 | -27,045 | RI | 569 | -155 | 415 | MA | 179 | -102 | 130 |
| CT | -24,865 | -3,596 | -25,301 | DE | 961 | -10 | 909 | MD | 247 | -175 | 201 |
| ME | -19,113 | -2,225 | -19,356 | MS | 1,899 | 452 | 2,873 | DE | 467 | -34 | 415 |
| NV | -16,116 | -1,631 | -16,342 | VT | 2,421 | 33 | 2,187 | NJ | 803 | -159 | 171 |
| MA | -16,032 | -1,881 | -16,251 | KY | 31,427 | 917 | 30,413 | TX | 15,590 | -550 | 11,057 |
| NH | -9,122 | -931 | -9,241 | GA | 34,639 | 1,230 | 33,541 | IN | 18,033 | 652 | 17,182 |
| RI | -6,645 | -1,016 | -6,852 | KS | 36,850 | 1,014 | 34,507 | ID | 19,187 | 801 | 18,535 |
| DE | -3,089 | -397 | -3,136 | NC | 38,855 | -885 | 36,464 | VA | 19,995 | -7,079 | 10,725 |
| DC | -200 | -47 | -221 | TX | 41,909 | 1,080 | 38,913 | GA | 24,633 | 425 | 23,689 |

**Note:** Simultaneously decreasing all ED, TC and TT by 20% as Scenario 2.

Table 9 shows the total-order effects of ED, TC, and TT on domestic and export trade flows, production, and consumption in the continental U.S. Similar to ED's first-order effects, ED's total-order effects are negative on all states' outputs when ED is lowered. In contrast, TC and TT have

much more complex total-order effects, moving in both negative and positive directions for domestic trade flows, export trade flows, production, and consumption across states.

Table 9 shows the total-order effects of ED, TC, and TT on domestic and export trade flows and consumption in the 20 continental U.S. states under Scenario 2. Similar to ED's first-order effects, ED's total-order effects are all negative on these outputs in all states, and ED's strongest total-order effects are on VA's domestic trade flows, export trade flows, and consumption. However, in VA, ED's total-order effects are smaller than ED's first-order effects were, on domestic trade flows and consumption, yet larger for export trade flow effects.

The strongest negative total-effects of TC and TT on domestic trade flows and consumption happen in NE, although the total-effects of TC and TT on export trade flows are positive.

By comparing the results under these two scenarios, one can conclude that first-order effects of ED are symmetric from the first-order of ED in Tables 4 and 7 because ED has the opposite signs of first-order effects with the same magnitudes on domestic trade flows, export trade flows, and consumption in 20 states. Other effects (excluding the first-order effects of ED) are not all symmetric, so the signs and/or magnitudes of the same effects under different scenarios differ across Tables 4 through 9.

## CONCLUSIONS AND EXTENSIONS

This paper uses the technique of LSAI to produce sensitivity indices for the variation of outputs, due to finite variations in model inputs to a complex model of production, consumption and trade flows across 3,109 U.S. counties. The work illustrates how LSAI applies to the RUBMRIO model of land use and transport, by simulating both the individual effect of every input and the interaction effects of inputs on outputs. More importantly, the work analyzes changes in production (via domestic trade flows and export demands) and consumption across the continental U.S.'s counties, tracking trade patterns among 12 socio-economic sectors and two freight modes (truck and rail).

LSAI offers a valuable set of relationships to enable policymakers, planners, and carriers to quickly predict trade flows by producers' location choices and production levels. LSAI offers the individual effects of inputs and their interaction effects on many types of models' outputs. LSAI enables analysts to clearly identify keydrivers for model predictions, and the magnitude and direction of changes in outputs, due to input changes and their interaction effects, which amplify or dampen individual effects of inputs.

Under scenarios developed here, LSAI techniques show how export demands (ED) are more important for accurately anticipating and quantifying U.S. trade flows than are transport costs and travel times (TC and TT). As expected, TC and TT effects typically carry the same sign or direction, with different magnitudes of first-order effect on domestic trade flows, production, and consumption in most states (e.g., KY by the first-order effects under Scenario 1). However, changes in TC and TT have opposing effects on outputs in some states. Tracking various inputs' effects helps policymakers, businesses, and carriers pursue more optimal policies, operations, and investments.

This type of LSAI investigation can be extended by varying EDs in each market/industry sector, and varying transport cost and travel time (TC and TT) values by route, link, and mode. The number of required simulations for LSAI application rise exponentially with the number of variable inputs and parameters, if one wishes to compute all interaction effects. Thus, the standard approach of many Monte Carlo simulations remains an important option. The use of congested network assignment for travel time and cost feedbacks (which vary by route, and by time of day and day of week), and application of the Bayesian Melding approach (which allows for dynamic forecasting, over time, but requires knowledge of intermediate-period outputs, for comparison) may provide useful extensions.

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# Exploring Sustainable Transportation Attitudes and Stages of Change Using Survey and Geospatial Data in New England Campus Commuters

**by Tat Fu, Norbert Mundorf, Colleen A. Redding, Leslie Brick, Andrea Paiva, and James Prochaska**

*This paper presents findings of a two-campus project designed to assess alternative/sustainable transportation (AT), which is defined as commuting via non-SOVs (single occupancy vehicles) such as transit, carpooling, walking, or biking. One of the objectives was to test the application of a well-known behavior change model, the Transtheoretical Model of Change (TTM), to transportation behaviors. Additionally, geospatial analysis and visualization were applied using the TTM measures. The survey results show that commuting distances, transit connectivity, and status (i.e., students, staff, and faculty) affected commute modes and stages of readiness to use AT. Another important finding was that the survey data for AT replicated TTM relationship predictions between constructs and stages of change.*

## INTRODUCTION

Due to disruptions prompted by demographic patterns, aging infrastructure, climate change, and a growing culture that values sustainability, there has been considerable interest in encouraging sustainable transportation alternatives. This quest has not yet translated into substantive behavior change. In order to achieve widespread adoption of alternative, active, sustainable transportation (AT) choices, population-based changes in individuals' knowledge, attitudes, and behaviors are essential. AT choices are transit, carpooling, walking, biking and other means of commuting without using single occupancy vehicles (SOVs).

Transportation has been the fastest-growing source of U.S. greenhouse gas emissions since 1990, and it contributes approximately 27% of greenhouse gas emissions in the U.S. (EPA 2006). It is also a primary source of pollution, traffic congestion, injury, and premature death. Many approaches are capable of reducing greenhouse gas emissions from transportation, such as developing energy efficient vehicles and tax incentives to promote alternative fuel (e.g., electric, hybrid, and natural gas) vehicles. However, a key strategy is the reduction of SOV miles traveled by shifting transportation modes to walking, biking, transit, and carpool. This will significantly and directly reduce the use of gasoline and car emission by reducing the number of cars on the road. This work was designed to assess and promote readiness for AT. In this project, two comparable transportation surveys were conducted among students, staff, and faculty at the University of New Hampshire (UNH) and the University of Rhode Island (URI). Comparative examination of survey results showed the differential impact of commute distances, geographic information, status, and stage of readiness for AT on commute patterns.

Surveys were conducted at both UNH and URI to assess transportation topics such as transit ridership, commute patterns, satisfaction and awareness of transportation services, traffic demand model measures, and parking. The surveys incorporated key measures of the Transtheoretical Model (TTM) with the primary goal of identifying differences in commuting behaviors among different university constituencies (students, staff, and faculty). Given that students typically live closer to campuses, the authors hypothesized that students would be more likely to display pro-AT attitudes and behaviors compared to staff and faculty. This hypothesis was tied to the second research goal,

which was to evaluate how geographical location affected commute behaviors. More specifically, the authors hypothesized that long commute distances discouraged the use of AT, and availability and proximity of public transportation infrastructure had a strong positive effect on AT usage.

The main contributions of this paper are to help promote the use of sustainable transportation by better understanding commuters' behaviors, attitudes, and their relationships to transit infrastructure and other location-based constraints. The study findings can be used by policy makers, school administrators, and city planners regarding transit infrastructure decisions. More specifically, attitudes, behaviors, and geographical information of commuters can be used to determine where and how to better allocate transportation resources and investment.

## BACKGROUND

### Transportation Modes

Transportation researchers and practitioners agree on the need to modify automobile transportation patterns—especially in urban areas, and during peak travel times. Also, resources to expand existing highways are severely limited—in fact, many states struggle to keep up maintenance of roads and bridges. A number of alternatives are being discussed. Travel Demand Management (TDM) experts point out that strategies, which "adjust roads and vehicles," have limited effectiveness as they often lead to increases in vehicle travel and associated problems (Litman 2015). Alternatively, addressing "market distortions" and, thus, influencing driver behavior may be a cost effective long-term strategy to reduce traffic congestion, crash risk, and pollution. Litman (2015) also points to several macro-economic trends, which also favor managing travel demand and promoting a shift to sustainable transportation alternatives, including rising costs of road construction, increased urbanization, aging demographics, consumer preferences, and environmental concerns.

Two recent articles in JTRF also address factors influencing Vehicle Miles Traveled (VMT). Woldeamanuel and Kent (2014) conducted an analysis of travel data in California and found that some key variables have remained as key factors (e.g. distance to work, population density), others gained significance compared with a decade earlier. In particular, commuting by public transit, and increasing public transit trips, as well as number of bike trips emerged as determinants of per capita VMT. McMullen and Eckstein (2013) studied 87 U.S. urban areas to analyze determinants of VMT. Among other findings, they found that the "per capita demand for VMT was … impacted by lane miles" (p. 5). They also found that fuel price and public transit use was negatively related to VMT. Overall, more western and larger urban areas were related to higher per capita VMT.

According to the Intergovernmental Panel on Climate Change (2013), transportation, especially by automobile, is one main contributor to greenhouse gas (GHG) emissions and the depletion of fossil fuel sources. Pacala and Socolow (2004) called for transportation related conservation strategies needed to mitigate climate change, pollution, congestion, and other problems. In addition, public health communities are increasingly concerned about the impact of sedentary lifestyles and energy balance. By reducing SOV usage, AT represents one effective way to simultaneously reduce GHG emissions and related threats, and increase physical activity (Dora 1999; Kwaśniewska et al. 2010; Woodcock, Banister, Edwards, Prentice, and Roberts 2007). Despite many synergistic benefits of sustainable transportation, nearly 90% of Americans still commute by driving alone.

Researchers have identified options to increase active transportation. A study commissioned by the American Public Health Association (2010) concluded that the near-complete dependence on automobile travel results in further costs of road construction and repair, continued urban sprawl and reduced walkability, less physical activity, health problems due to sedentary lifestyle, pollution and car crashes, and enormous long-term direct and indirect costs. Morency, Demers, and Polinquin (2014) found that converting short motorized trips to walking would allow 8.3% of their study population to increase physical activity levels, potentially improving weight management.

Underwood, Handy, Paternity, and Lee (2014) conducted a detailed interview study and concluded that biking was somewhat popular among American elementary school children, but tended to lose interest once they entered middle school. While numerous political, social, economic, structural, and cultural factors need to be considered in order to change the overreliance on SOV driving, communication strategies aimed at behavior change will provide critical engagement and incentives.

Sheepers et al. (2014) analyzed various incentives designed to promote active transportation as a way to encourage physical activity and reduce negative impacts of SOV transportation. Almost all studies in their analysis of published research found positive effects on (sustainable) mode shift from car use to active transportation. They categorized intervention tools as legal, economic, communicative (media, behavioral) or physical (e.g., bike rentals, improved facilities). Typically, more than one intervention tool was used, such as social marketing, individualized transportation plans, improved facilities, or financial incentives.

**Transtheoretical Model**

The Transtheoretical Model (TTM) has been recognized as one of the world's leading approaches to changing health behaviors. TTM has been successfully applied to more than 50 health behaviors (Hall and Rossi 2008), including smoking, diet, and exercise. Interventions based on the TTM have been successful at moving entire populations, including people who are not interested in moving toward change and in encouraging people to sustain long-term behavior changes (Noar, Benac, and Harris 2007; Krebs, Prochaska, and Rossi 2010; Prochaska, Redding, and Evers 2008). Smoking cessation is the most widely studied behavior change using the TTM, with measurement development research (Redding, Maddock, and Rossi 2006) leading to tailored intervention development and randomized trials evaluating the efficacy of TTM interventions (Prochaska, DiClemente, Velicer, and Rossi 1993; Velicer et al. 1999). Finally, TTM intervention efficacy with smoking cessation has also been replicated and extended in new populations and with multiple behavioral targets, including some studies by independent investigators (Hall et al. 2006; Hollis et al. 2005; Prochaska et al. 2001, 2004, 2005). This program of research for smoking cessation and other health behaviors provides direction and promise for TTM research applied to sustainable transportation. In order to systematically develop instruments and interventions to promote change in individual's transportation behavior, TTM and geospatial modeling were used to compare transportation choices and behaviors at two New England state universities with considerable variation in transportation infrastructure and travel patterns.

One key construct of the TTM is the *stage of change***.** Longitudinal studies have found that people move through a series of five stages when modifying behavior on their own or with the help of formal intervention (Prochaska and DiClemente 1983; Prochaska et al. 2008). In *precontemplation*, individuals may deny a problem and be resistant to change; they may be unaware of the negative consequences of their behavior, or have given up on change because they are demoralized. They are not intending to change in the foreseeable future. Individuals in *contemplation* are more likely to recognize the benefits of changing. However, they continue to overestimate the costs of changing and, therefore, are ambivalent and not yet ready. Individuals in *preparation* have decided to change soon, and have begun to take small steps toward that goal. People in *action* are overtly engaged in modifying their behavior and are working to prevent relapse. Those in *maintenance* have sustained change for at least six months and may not need to work as hard to prevent relapse as their behavior change becomes more habitual. The TTM improves the likelihood of behavior changes by tailoring or targeting interventions to each individual's *stage of change*. The TTM also includes constructs such as decisional balance and self-efficacy that have demonstrated systematic relationships with stages of change (Hall and Rossi 2008). Decisional balance, specifically, addresses individuals' evaluations of the costs of changing, and/or the cost savings of adopting a new behavior. These TTM constructs have been adapted and applied to sustainable transportation (Redding et al. 2015). Meta-

analyses across a series of randomized trials including a range of different health behaviors have found that TTM tailored interventions are more effective than non-tailored interventions (Krebs et al. 2010; Noar et al. 2007).

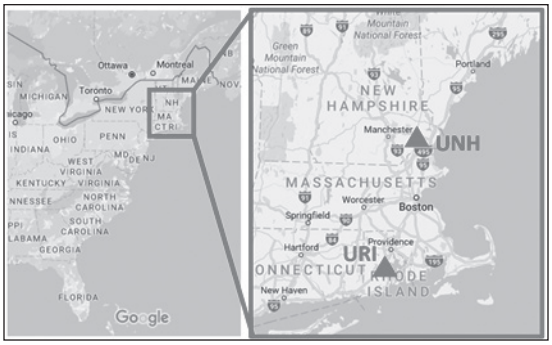
A TTM-based intervention study in the U.K. to increase active commuting among employees was effective. Mutrie et al. (2002) demonstrated that a TTM-based self-help intervention effectively helped those people who were either in the contemplation or preparation stages to initiate active commuting (walking or bicycle riding) to work.

Two Australian studies demonstrated the potential utility of TTM in reducing single occupancy vehicle (SOV) as a primary mode of transportation. Shannon et al. (2006) assessed the potential for change as well as barriers and motivators affecting transportation choices of 1,040 students and 1,170 staff at the University of Western Australia in Perth. A strong predictable relationship between stages of change for adopting active modes of transportation (walking, biking, public transit use) and pros and cons of change and self-efficacy (confidence in using active modes) was demonstrated. Students (46.8%) and staff (21.5%) engaged in "active modes" of transportation. Attitude and behavior patterns were more favorable compared with the U.S., but they also illustrated the potential for reaching out to those not yet engaged in active modes of transportation.

Rose (2008) utilized a software package, *TravelSmart,* to target 2,977 incoming students at Monash University, Australia, to encourage the use of AT modes and reduce SOV travel. Students received individually tailored travel information as well as various incentives. A single tailored intervention produced progress for those at each stage of change over the course of the school year.

**UNH and URI Campuses**

**Figure 1: UNH and URI Locations**
(base image from Google Map®)




UNH's main campus is located in Durham, NH (Figure 1), with 14,467 students and 3,577 staff and faculty. UNH has a good public transportation system and a well-established culture of sustainability. According to the 2007 UNH Transportation Report (UNH 2007), UNH Transit provided over one million transit trips to the surrounding community in 2006-2007, making UNH the largest transit system in the state and significantly reducing SOV miles traveled. Over 50% of off-campus students lived within walking distance of a UNH transit stop and only half of off-campus students commuted by driving alone. On the other hand, most staff and faculty commuted by SOVs.

There are three nearby towns (5-11 miles away) in the UNH Durham campus area— Dover, Newmarket, and Portsmouth. UNH Transit covers these towns with frequent schedules, providing convenient transportation alternatives to students, staff, and faculty living there. Rochester and Exeter are two other towns nearby (12-15 miles away) with limited transit options to the Durham campus. Manchester and Concord (35-40 miles away) are two urban centers housing many UNH commuters. Some UNH personnel also commute from Massachusetts and Maine.

URI's main campus is located in South Kingstown, RI (Figure 1), with 16,294 students and 2,543 staff and faculty. The town has the third-largest commuter population among RI state employees—many of them URI staff and faculty. Underclassmen tend to live in campus housing. Most off-campus students live in Narragansett, often in winter rentals near beaches and coastal recreation areas. Due to zoning, there is very little off-campus student housing in South Kingstown, which means that a typical commute for off-campus students from Narragansett is between 5-8

miles, just beyond comfortable biking range. In-state commuters often travel from their homes throughout the state. Public transportation to URI is limited in availability and usage. Buses are operated by the Rhode Island Public Transportation Authority. Transit connectivity between URI and RI communities is limited: one bus line connects with the capital of Providence (30 miles away) and continues to the southern part of South Kingstown. Another line connects URI with its Bay Campus in Narragansett and the city of Newport (18 miles away). Buses run about hourly with limited evening service. Coordination with class schedules is very limited. The most suitable form of AT for most off-campus students would be carpooling. There is virtually no transit connectivity to the western and southwestern part of the state.

This collaboration between URI and UNH provided a unique opportunity to examine transportation behaviors and attitudes using the TTM. UNH has a good public transportation system and, in spite of a well-established culture of sustainability, faculty and staff are still reluctant to use AT. URI has limited public transportation connectivity and has only recently begun to embrace sustainability, so faculty, staff, and off-campus commuters are also reluctant to use AT. Examined using the TTM, this may mean that participants are at different stages of change for AT and/or that participants value the pros and cons of AT differently. It also means that external conditions for change are more favorable at UNH. Both campuses may require different tailoring of interventions. A comparative study has value in adapting this model to changing transportation behaviors.

## METHOD

### Sample and Recruitment

The target population consists of 14,469 UNH students, 3,577 UNH staff and faculty, 16,294 URI students and 2,543 URI staff and faculty studying and/or working at the main Durham (UNH) and South Kingston (URI) campuses. Visitors were also welcome to participate in the surveys. Both UNH's and URI's institutional review boards approved all procedures for compliance with human subjects' considerations. Data were collected in spring 2011 over a four-week period in April and May to minimize the impact of New England weather and holidays.

Both online and phone surveys were used at UNH, while online surveys only were used at URI. Online surveys were conducted using a popular online surveying website. UNH phone surveys were conducted through UNH's Survey Center targeting only staff and faculty. A list of staff and faculty office phone numbers were obtained from UNH's human resources department and the staff at the Survey Center called a random sample of these phone numbers to recruit a target sample of 400 participants. Phone surveys were much more costly compared with online surveys but they could target a specific group of participants. In prior UNH transportation surveys, staff and faculty were recruited using phone surveys, and the 2011 survey continued this recruitment method for longitudinal comparison purposes. The 2011 survey was URI's first campus-wide transportation survey, and resources were not available to conduct phone surveys.

Newsletters, email, and social media advertisements were the main recruiting methods for the online survey at UNH. Flyers were also posted throughout the UNH campus. Incentives were also used. UNH survey participants could win prizes while URI recruitment included emails and class announcements to participate in an anonymous, voluntary online survey. Several email announcements were sent to the campus community, and a link was posted on the campus website. In addition, departments approached their faculty and staff to encourage participation. Students were reached by web and email. In a number of classes, students received extra credit or research credit for survey participation.

**Survey Description and Development**

The UNH and URI 2011 transportation surveys were a collaboration between UNH and URI. Since 2001, UNH has regularly conducted campus-wide transportation surveys with the most recent prior data collected in 2007. The 2011 surveys were adapted based on this 2007 UNH Transportation Survey (UNH 2007) by adding TTM measures for AT (Redding et al. 2015). The goals of past surveys were to assess community attitudes regarding UNH's transportation system, campus mobility, and accessibility issues. Questions from past surveys were repeated to allow longitudinal comparisons. The 2011 surveys covered transportation topics such as transit ridership, commute patterns, satisfaction and awareness of transportation services, traffic demand model measures, and parking. The URI survey was adapted to reflect the uniqueness of the campus and transportation system. Comparable questions were included in both surveys to facilitate comparison between the two campuses.

**Measures**

**Stages of Change for Alternative Transportation.** Stages of change for AT was assessed using the following item, consistent with prior research (Redding et al. 2015): "Alternative transportation includes any way of getting to URI or UNH other than driving by yourself (single occupancy vehicle use). So walking, biking, public transportation (bus/subway/train) and carpooling are all means of Alternative Transportation." Then, participants chose one statement that best reflected their situation:

(1) I do not regularly use AT and I do not intend to start within the next six months (Precontemplation);
(2) I am thinking about using AT regularly within the next six months (Contemplation);
(3) I plan to use AT regularly within the next 30 days (Preparation);
(4) I use AT regularly and have been for less than six months (Action); or
(5) I use AT regularly and have for six months or more (Maintenance)

**Decisional Balance for Alternative Transportation.** A decisional balance measure assessing pros and cons of Alternative Transportation (AT) reported good measurement structure, assessed by principal components and structural equations modeling analyses (Redding, Maddock, and Rossi 2006), and replicated previously established relationships with stages of change in college students, staff, and faculty (Redding et al. 2015). More specifically, the pros (5-item $\alpha = .84$) and cons (5-item $\alpha = .77$) each showed a relatively high value for Cronbach's alpha, $\alpha$, which is a measure of internal consistency (Cronbach 1951). SPSS 21 was used to calculate $\alpha$ as described in Redding et al. (2015). Pro items asked individuals to weight the importance of various AT benefits in their own decision making, including such potential benefits as saving money, being green, and improving their own and the planet's health. Along similar lines, con items asked participants to weight the importance of various downsides of AT in their own decision making, including such potential barriers as time, practicality, and difficulty.

**Self-Efficacy for Alternative Transportation.** A five-item self-efficacy scale ($\alpha = .82$ as computed in SPSS 21) also reported good measurement properties (Redding et al. 2006) and replicated hypothesized relationships with stages of change in college students, staff, and faculty (Redding et al. 2015). Self-efficacy items asked participants to rate how confident they were that they would use AT, even when challenges arose, such as when they were running late, it was inconvenient, or they were tired.

**Geospatial Variables.** Survey participants (off-campus residents) were asked to enter address information of their residence—the closest cross streets and zip codes. Such information is used to obtain geographic information such as longitudes and latitudes. Due to privacy concerns, only

the closest cross streets of participants' residences were requested. Given that block sizes varies in different towns and individuals' variation in identifying the nearest cross streets, the authors acknowledge the inherent errors in this method of collecting geospatial information.

The geospatial variables were calculated with the self-reported closest cross streets of participants' residences. Given the uneven distribution of residence locations, the geospatial analyses are based on scattered points instead of uniformly spaced grid points. Spatial gaps, such as unpopulated regions, were automatically excluded as there are no survey data in these areas.

### Statistical Analyses

First, demographic, site, and subgroup descriptive and transportation variables were examined systematically prior to geospatial analyses. All statistical analyses were conducted using SPSS 21. A three-way Multivariate Analysis of Variance (MANOVA) was conducted among off-campus participants to examine the effects of study site (UNH, URI), employment group (students, faculty/staff), and AT stage on three dependent variables: pros, cons, and self-efficacy. Subsequent follow-up ANOVAs were conducted to clarify interpretation (Tabachnick and Fidell 2013). To balance sample sizes across subgroups, the AT stages were collapsed into three groups (Precontemplation, Contemplation/Preparation, Action/Maintenance), and staff and faculty were combined into one group. All analyses summarize effect sizes using $\eta^2$ (eta-squared), an effect size measure, comparable to $R^2$ used for regression, that shows the proportion of variance accounted for by the effect being tested (Tabachnick and Fidell 2013). Effect size estimates, such as $\eta^2$, are interpreted using guidelines for small (.01), medium (.06), and large (.14) effects developed by Cohen (1988).

### Geospatial Analyses

Two main types of geospatial analyses are presented. One is a simple representation of variables in a geographic format (i.e., on a map). Such representations can show concentrations of data points (e.g., public transit commuters living in towns with good public transportation options). Another analysis requires spatial averaging of variable values. The averages were calculated within a 2-mile × 2-mile area centered at participants' residences. A 2 × 2 mile$^2$ area is used because it covers a one-mile radius from the center point. Finer (e.g., 1 × 1 mile$^2$) or coarser (e.g., 3 × 3 mile$^2$) scales can be used to produce more localized or generalized spatial averages, respectively. Spatial averaging can help describe trends or patterns in different regions such as the average age of a town's residents. However, similar to most averaging methods, spatial averaging can be skewed by outliers, especially in regions with few responses.

## RESULTS

### Survey Sample

A total of 1,868 subjects participated in the UNH and URI transportation survey in spring 2011 (1,111 subjects at UNH and 757 at URI). Table 1 presents demographics of survey participants. There were more female participants than males in both surveys, and URI had a higher percentage of female participants than UNH. URI participants were younger with an average of 28.06 years old compared with the UNH average of 40.1 years old. This age difference partially reflected the fact that staff was the largest group (52%) at UNH while students comprised the largest group (66%) at URI. Participants who were both employed by the universities and taking courses were typically graduate students. At both UNH and URI, most participants were off-campus residents, living away from the Durham (84.5%) or Kingston campus (72%). Over 80% of participants self-identified as white on both campuses. AT stage distributions reveal that for both locations, the largest stage was precontemplation (66.8% for UNH and 62.9% for URI), but that stage was not distributed equally

across sites, $\chi^2$ (4) = 28.96, $p$<0.0001, $\phi$=0.14. Surprisingly, more UNH participants were in PC and C and fewer in M, compared with URI participants.

**Table 1: SurveyDemographics by Site**

| | UNH | | URI | |
|---|---|---|---|---|
| | N* | % | N* | % |
| **Gender** | | | | |
| Male | 465 | 43.6% | 261 | 36.2% |
| Female | 601 | 56.4% | 459 | 63.8% |
| **Age** | | | | |
| Mean | 40.1 | | 28.06 | |
| Standard Deviation | 15.6 | | 13.7 | |
| Range | 18-98 | | 18-74 | |
| **Status** | | | | |
| Student | 310 | 27.9% | 551 | 66.0% |
| Faculty | 137 | 12.3% | 87 | 10.4% |
| Staff | 578 | 52.0% | 136 | 16.3% |
| Employed and Taking Classes | 67 | 6.0% | 32 | 3.8% |
| Visitors or others | 19 | 1.7% | 29 | 3.5% |
| **Residence** | | | | |
| On-campus residents | 172 | 15.5% | 212 | 28.0% |
| Off-campus residents | 939 | 84.5% | 545 | 72.0% |
| **Ethnicity** | | | | |
| White | 591 | 83.2% | 646 | 89.7% |
| Black or African American | 2 | 0.3% | 22 | 3.1% |
| Asian | 29 | 4.1% | 11 | 1.5% |
| Hispanic Latino | 8 | 1.1% | 22 | 3.1% |
| Native Hawaiian or Other Pacific Islander | 3 | 0.4% | 1 | 0.1% |
| American Indian or Alaska Native | 2 | 0.3% | 3 | 0.4% |
| Other | 75 | 10.6% | 15 | 2.1% |
| **AT Stage Distribution (Off-campus residents)** | | | | |
| Precontemplation (PC) | 364 | 66.80% | 573 | 62.90% |
| Contemplation (C) | 91 | 16.70% | 94 | 10.30% |
| Preparation (PR) | 15 | 2.80% | 45 | 4.90% |
| Action (A) | 18 | 3.30% | 34 | 3.70% |
| Maintenance (M) | 57 | 10.50% | 165 | 18.10% |

* Slightly different *N*'s across categories reflect missing data

**Commuting Modes**

Figure 2 breaks down the main commuting modes at UNH and URI among students, staff and faculty. Students used AT much more often than staff and faculty at both campuses. At UNH, only 35% of students drove alone to school compared with faculty (74%) and staff (84%). All URI commuters used SOV at higher levels than UNH commuters. URI students commuted by SOVs at 53%, and URI faculty and staff were at 82% and 85%, respectively.

Students showed the largest between campus difference (18%) using AT among all statuses. At UNH, 31% of students walked or biked to school compared with 25% of URI students. Almost a quarter (24%) of UNH students rode university transit. In comparison, only 9% of URI students reported using university or public transit. On the other hand, URI students carpooled (13%) more frequently than UNH students (9%) did.

At UNH, significantly fewer faculty (74%) drove alone to campus compared with staff (84%). Meanwhile, comparable proportions of URI faculty and staff drove alone to work (82% of faculty and 85% of staff). UNH faculty (25%) used AT more often than their URI counterparts (17%). More UNH faculty walked, biked, and rode public transit than URI faculty. For staff, UNH (84%) and URI (85%) showed similar AT usage. UNH staff walked more and URI staff took public transit more often. At both campuses, faculty used AT more often than staff. This observation aligns with a previous study that found less education was associated with greater gasoline consumption (Liu 2007).

**Figure 2: Main Commute Modes by Status**

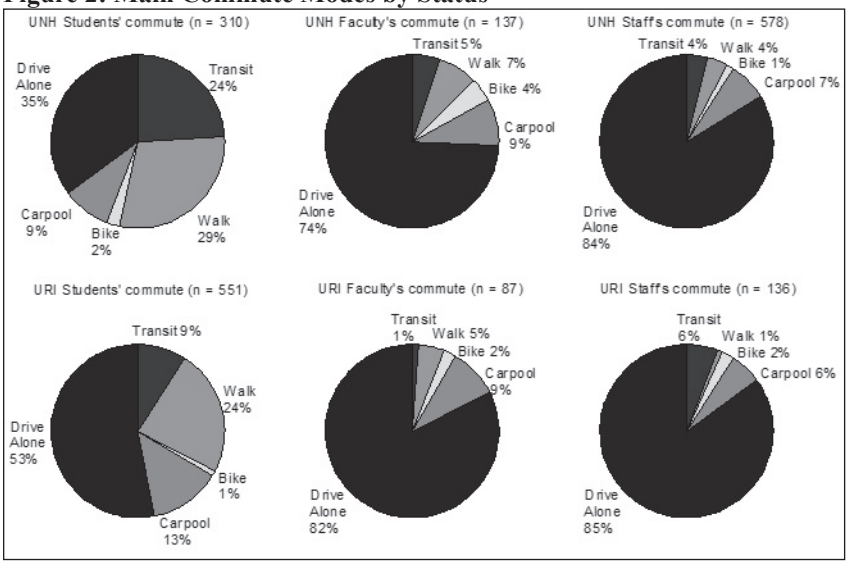



Figure 3 illustrates the average commute distances by off-campus student, faculty, and staff residents at UNH and URI. At UNH, students lived closest to campus followed by faculty and staff, who lived the farthest. At URI, students also lived the closest to campus while faculty and staff lived similar distances from campus. Across all subgroups, UNH commuters lived closer to campus compared with URI commuters.

**Figure 3: Off-campus Residents' Commute Distances by Site**

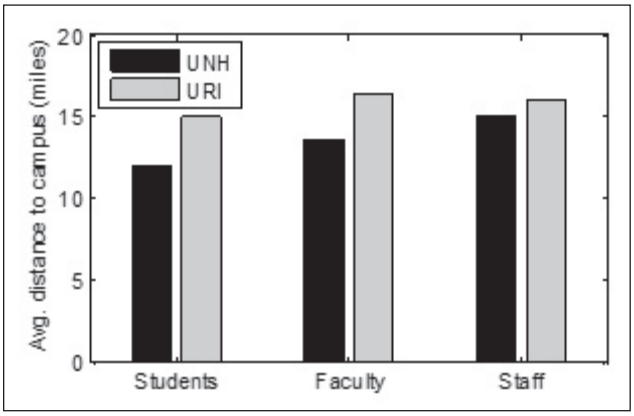



**Figure 4: Off-campus Residents' Main Commute Modes and Average Commute Distances**

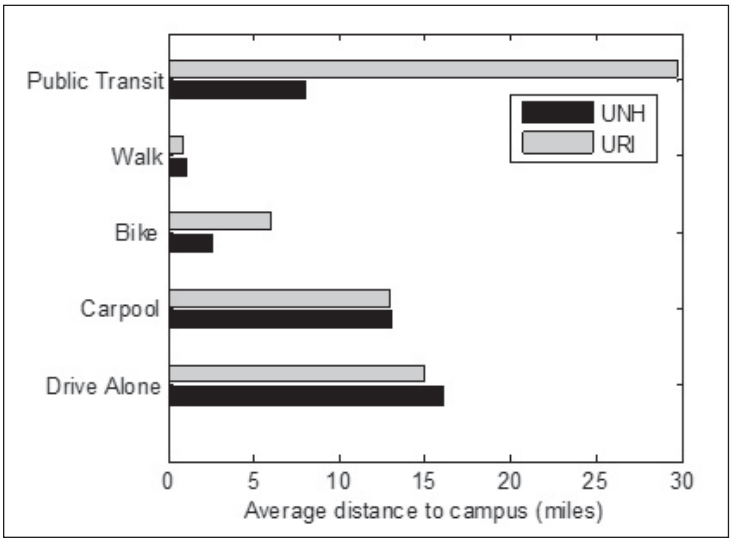
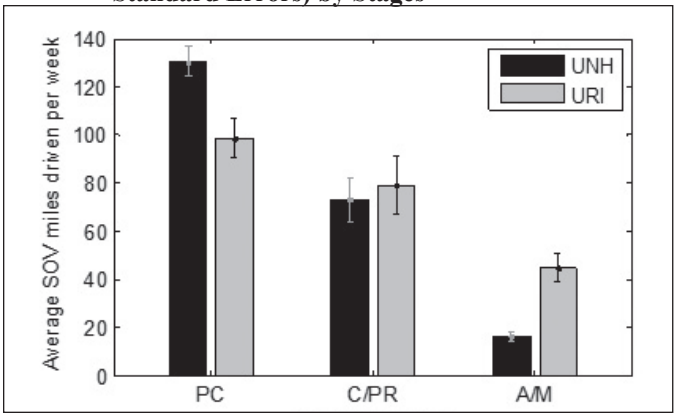



**Figure 5: Average Weekly SOV Miles Driven (with Standard Errors) by Stages**



We hypothesized that commute distances had an impact on commuting choices. In Figure 4, main commute modes were compared to commute distances for UNH and URI, respectively. At both UNH and URI, average commute distances followed similar trends for four commute modes: SOV, carpooling, biking, and walking. Among these four modes, SOV commuters live the farthest from campus, followed by carpooling and biking commuters. Walking commuters live the shortest distances from both campuses. UNH and URI commuters who used public transit had different commute distances. The average commute distance of UNH's "Public Transit" mode was in between "Bike" and "Carpool" distances. At URI, commuters who rode public transit had the longest commute distance at 27.5 miles.

**Geographical Locations**

To examine the relationships between AT stages of change, site (UNH, URI), and SOV miles driven, we conducted a two-way (by site and stage) ANOVA on average weekly SOV miles driven and graphed weekly SOV miles driven by both site and stage (see Figure 5). This ANOVA found a small significant site by stage interaction ($F$ (2,972) = 7.70, $p$<.001, $\eta^2$=.015, a significant medium-to-large sized main effect for stage, ($F$ (2,972) =53.06, $p$<.001, $\eta^2$ = .088, but no significant main effect for site. Figure 5 shows how many SOV miles were driven in an average week by all Stage groups at both sites (UNH, URI). Figure 5 also shows that, for participants in PC, UNH participants drove more SOV miles per week, while for participants in A/M, URI participants drove more SOV miles.

The stages of change for AT were also plotted geographically (Figures 6 and 7 for UNH and URI respectively). Each square in the figures represents the average value of the stages in a 2-mile × 2-mile area with a value of 1 for the *Precontemplation* (P) stage, 2 for *Contemplation* (C), 3 for *Preparation* (PR), 4 for *Action* (A), and 5 for *Maintenance* (M). A high average stage value indicates higher levels of readiness to use AT by the residents living in this square area; a low average stage value reflects residents' lower levels of readiness for using AT.

At UNH (Figure 6), the stage values were the highest (in A) in Durham, close to campus, reflecting that the many residents in this area were actively using AT. In the three nearby towns (Dover, Portsmouth, and Newmarket) that are covered by UNH transit, the stage values were also high. Portsmouth and Newmarket commuters were mainly in P while Dover was slightly earlier, typically in C/PR. For other nearby towns without university transit coverage, residents at Rochester had higher stage values (slightly above C) compared with Exeter (PC/C). Manchester and Concord residents were mostly in P. Generally, areas far away from campus had earlier average stage levels. However, certain less populated areas had relatively high average stage values despite being far from campus; this is likely due to the small number of data points in these areas.

At URI (Figure 7), there were four towns with average stage values well above PR: Kingston, Providence, Newport, and South Kingstown. All four towns had similar average stage values in between C and PR. Providence residents had the highest stage values. South Kingstown was separated into two regions with different stage values. The east part of South Kingstown was in PC/C while the west part was closer to PR. There were individual areas with M values but they consist of single data points. Similar to UNH, sparsely populated areas that were far away from campus had lower average stage values.

**Multivariate Analysis of Variance of TTM Constructs**

To compare attitudes toward AT and AT efficacy across campus sites and faculty/staff/student subgroups at different stages of change, a three-way MANOVA among off-campus participants examined the effects of site (UNH, URI), employment status (student, faculty/staff), and AT stage (precontemplation, contemplation/preparation, and action/maintenance) on three TTM dependent variables: AT pros, AT cons, and AT self-efficacy. Standardizing dependent variable scores allowed

**Figure 6: UNH AT Stages by Locations (Off-campus Residents Only); Notation: Precontemplation (PC), Contemplation (C), Preparation (PR), Action (A), Maintenance (M); Base Image from Google Earth®**

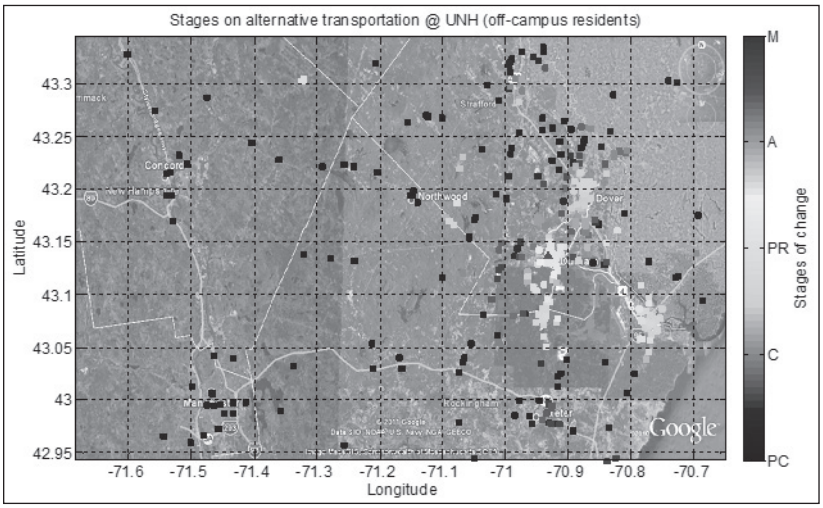
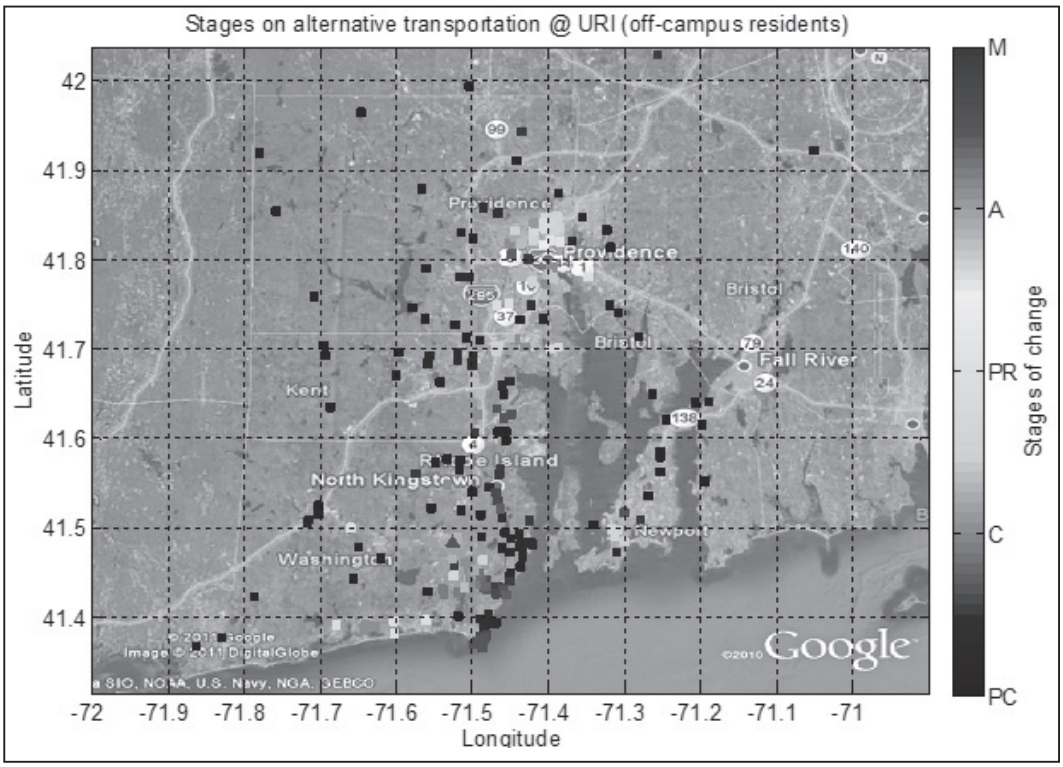



**Figure 7: URI AT Stages by Locations (Off-campus Residents Only); Notation: Precontemplation (PC), Contemplation (C), Preparation (PR), Action (A), Maintenance (M); Base Image from Google Earth®**



for direct comparisons across constructs that may have different standard deviations (Hall and Rossi 2008), thus T-scores, similar to z-scores, standardize measures based on standard deviation units. Table 2 and Figure 8 present standardized (T-scores M=50, SD=10) mean scores by stage, site, and employment status for pros, cons, and self-efficacy. Comparable to the F-test statistic used for ANOVA, and similar to Wilk's Lambda, a test statistic used for MANOVA, Pillai's Trace test statistic was used for MANOVA significance testing here to adjust for a violation of homogeneity of covariance matrices. All three main effects (site, employment status, stage) achieved significance with no significant two-way or three-way interaction effects. Eta-squared ($\eta^2$) is a measure of effect size with established guidelines (Cohen 1988; Tabachnick and Fidell 2013). A small overall main effect was found for site, *Pillai's Trace* = .011, $F$ (3, 1146) = 4.333, $p$ = .005, $\eta^2$ = .011; a medium-to-large main effect was found for stage, *Pillai's Trace*=.190, $F$(6, 2294)=40.060, $p$<.001, $\eta^2$=.095; and finally, a small main effect was found for employment status, *Pillai's Trace* = .008, $F$ (3, 1146) = 2.964, $p$ = .031, $\eta^2$ = .008.

Table 2 and Figure 8 show mean T-score differences across all of these subgroups. Finally, three separate three-way follow-up ANOVAs examined each dependent variable one at a time: AT pros, cons, and self-efficacy by site, employment status, and stage to clarify multivariate findings reported above. To control for conducting multiple separate tests that would inflate the alpha level, a Bonferroni adjustment ($\alpha$ = .05 divided by 3 tests: $\alpha$ = .017 for each of three dependent variables) was used (Tabachnick and Fidell 2013). Significant small differences were found for the AT cons scale by site, $F$ (1, 1158) = 12.074, $p$ = .001, $\eta^2$=.010, with UNH scoring lower than URI. The small effect for employment status for AT pros approached significance, $F$ (1, 1158) = 4.132, $p$ = .042, $\eta^2$= .004, but after Bonferoni adjustment, was no longer significant. Significant medium-to-large differences were found for AT cons by stage, $F$ (2, 1157) = 90.598, $p$ < .001, $\eta^2$ = .136, with participants in A/M scoring lowest, followed by C/PR, and then PC; significant medium sized differences for AT pros by stage, $F$ (2, 1157) = 28.762, $p$< .001, $\eta^2$=.048, with PC lower than A/M and C/PR; and medium-to-large differences for AT self-efficacy by stage, $F$ (2, 1157) = 58.136, $p$ < .001, $\eta^2$ = .092, with PC scoring lowest, followed by C/PR, and then A/M. In summary, these patterns of effects found (see Table 2 and Figure 8) for AT pros, AT cons, and AT self-efficacy across AT Stages of change were consistent across both UNH and URI sites, and across student and faculty/staff subgroups.

**Figure 8: Means T-scores by Stage, Site, and Employment for TTM Measures; Notation: Precontemplation (PC), Contemplation/Preparation(C/PR), Action/Maintenance (A/M).**

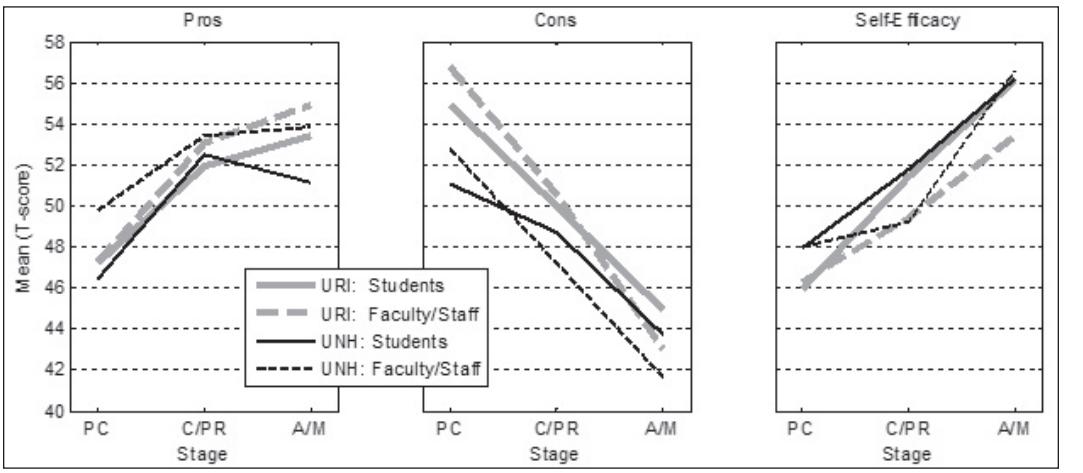


**Table 2: Off-campus Students and Faculty/Staff Mean (SD) T-scores by Site and Stage; Notation: Precontemplation (PC), Contemplation/Preparation(C/PR), Action/Maintenance (A/M)**

| Study Location | Measure | Stage | Student | | | Staff/Faculty | | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean | SD | *N* | Mean | SD | *N* |
| URI | Pros | PC | 47.25 | 8.90 | 201 | 47.30 | 11.93 | 96 |
| | | C/PR | 51.95 | 8.11 | 59 | 53.06 | 10.04 | 27 |
| | | A/M | 53.44 | 9.63 | 36 | 54.90 | 8.71 | 28 |
| | Cons | PC | 54.92 | 8.16 | 201 | 56.72 | 8.11 | 96 |
| | | C/PR | 50.03 | 8.20 | 59 | 50.58 | 6.45 | 27 |
| | | A/M | 44.97 | 11.71 | 36 | 43.01 | 10.64 | 28 |
| | Self-Efficacy | PC | 45.95 | 8.72 | 201 | 46.33 | 8.92 | 96 |
| | | C/PR | 51.39 | 7.63 | 59 | 49.44 | 7.82 | 27 |
| | | A/M | 56.08 | 11.57 | 36 | 53.43 | 9.05 | 28 |
| UNH | Pros | PC | 46.47 | 10.75 | 63 | 49.79 | 10.40 | 385 |
| | | C/PR | 52.47 | 10.16 | 26 | 53.41 | 7.74 | 85 |
| | | A/M | 51.15 | 10.48 | 69 | 53.86 | 9.14 | 85 |
| | Cons | PC | 51.07 | 7.86 | 63 | 52.80 | 9.01 | 385 |
| | | C/PR | 48.71 | 9.32 | 26 | 47.24 | 9.33 | 85 |
| | | A/M | 43.75 | 10.96 | 69 | 41.70 | 10.03 | 85 |
| | Self-Efficacy | PC | 47.93 | 9.42 | 63 | 48.00 | 8.83 | 385 |
| | | C/PR | 51.77 | 9.65 | 26 | 49.22 | 8.16 | 85 |
| | | A/M | 56.19 | 9.44 | 69 | 56.62 | 11.03 | 85 |

## DISCUSSION

This integration of transportation and behavioral science research has demonstrated that both fields contribute important insights toward an improved understanding of transportation choices and ultimately the promotion of active, sustainable transportation. Commute distances and transportation infrastructure at both universities strongly influenced commute choices, attitudes, and readiness for alternative transportation (AT).

The results of UNH and URI's 2011 transportation surveys showed that students, staff and faculty displayed somewhat different commute behaviors at both universities. Figure 2 showed that students used AT more often than staff and faculty at both universities. This was largely due to the fact that students were more likely to live on campus. It is also possible that students' attitudes were more green compared with faculty/staff, although we did not find stronger endorsement of the pros of AT among students compared with faculty/staff (see Table 2). It is possible that we had a more select sample of faculty/staff with more green attitudes, given much higher numbers of and participation rates among students. Even among off-campus residents only, positive and negative attitudes toward AT were much more strongly related to the stage of change for AT than student/faculty/staff status or campus site. In fact, stage of readiness for AT accounted for about 8.8% of weekly SOV miles traveled and about 10% of the variance in attitudes and efficacy to use AT, and these results were consistent across students and faculty/staff groups, as well as across campuses. In fact, the relationships between AT stage and AT pros, cons, and self-efficacy replicated well across campus and student/faculty/staff subgroups in this study and replicated prior results as well (Redding et al. 2015). Campus did show a small effect on attitudes with participants at UNH rating

the cons of AT lower than participants at URI. This may reflect the more facilitative transportation infrastructure and culture of sustainability at UNH compared with URI. At UNH, 41.5% of students lived on campus while only 2.5% of staff and faculty lived on campus. At URI, 29.4% of students lived on campus while almost no staff or faculty (0.6%) did. Even among off-campus residents, students tended to live closer to campus than staff and faculty (Figure 3). Given that there were more on-campus UNH student residents (Table 1), and UNH off-campus student residents lived closer to campus compared with URI students (Figure 3), Figure 2 also showed that more UNH students used AT than their URI counterparts did.

Commute behaviors were also different between staff and faculty as a function of commute distances. Figure 3 showed that at UNH, faculty lived closer to campus compared with staff, and more faculty used AT than did staff. At URI, faculty and staff lived at similar distances from campus, and there was only a very small difference (3%) between faculty and staff in using AT.

Figure 4 further supported the hypothesis that long commute distances discouraged AT usage. SOV commuters had the longest commutes (17 miles at UNH and 15 miles at URI) compared with all other commuters using AT. A single exception was the category of public transit commuters at URI. This exception was largely due to two popular public transit routes from Providence (30 miles away) and Newport (18 miles away) to URI. This showed that, in addition to commute distances, well placed public transportation infrastructure can support AT behaviors.

In UNH's nearby towns (Dover, Portsmouth, and Newmarket), there is an excellent UNH transit system and many residents commuted by transit. At URI, many Providence and Newport residents (mostly students) rode public transit to campus. Given that UNH transit is free to UNH commuters and its covered towns are relatively close (5-11 miles) to campus, more UNH commuters chose transit (24% of students and 4.8% of staff and faulty) compared with URI commuters (9% of students and 4.1% of staff and faulty). This presents an opportunity for URI in the future to improve its transit infrastructure.

The TTM measures also showed that commute distance and public transportation infrastructure influenced AT behaviors and attitudes. Figure 5 showed evidence of construct validation of the AT stages of change measure on commuting patterns; it showed that participants who were in later stages of change, that is, those practicing AT, drove fewer SOV miles at both campuses, as would be expected. This effect of stages of change on weekly SOV miles traveled appeared stronger at UNH given the steeper slope in Figure 5 for UNH compared with URI, where sustainability support and infrastructure is stronger. These conclusions confirmed our initial hypotheses and show how AT stage can be useful, especially when combined with other transportation measures, in future efforts to improve active and sustainable transportation. Figures 6 and 7 showed an overall trend of more readiness for AT at shorter commute distances on both campuses. These figures also displayed higher levels of AT stage when commuting from towns (Dover, Portsmouth, and Newmarket in NH and Providence and Newport at RI) with adequate public transportation infrastructure.

Finally, multivariate analyses on the entire sample found a significant relationship between AT stage and the three TTM constructs (AT pros, cons, and self-efficacy). These significant stage differences found were consistent with TTM theoretical predictions and replicated previous research findings across a range of health behaviors (Hall and Rossi 2008; Prochaska et al. 2008) and one previous study on transportation behaviors (Redding et al. 2015). Table 2 and Figure 8 show that participants in A/M scored lowest for cons but highest for self-efficacy, and participants in PC scored lower than C/PR and A/M for pros, lowest for self-efficacy, and highest for cons. Future research may find a better distribution of individuals across AT stage subgroups; small sample sizes in some subgroups limited our ability to compare all stage groups with sufficient power. Future studies should also examine longitudinal changes in AT attitudes and behaviors.

## Conclusion and Future Work

Promotion of alternative, active modes of transportation (AT), such as walking, biking, carpooling, and public transit, can significantly improve sustainability on and off campus. There are many barriers for commuters to choose AT, such as long commute distances and inconvenient public transportation options. Understanding the commute behaviors and decision-making processes for choosing commuting modes is essential to effectively encourage AT. Transportation surveys conducted at two New England universities, UNH and URI, integrated behavioral and attitudinal measures—Transtheoretical Model (TTM)—and geographical information queries (e.g., residence locations) to assess AT stages of change, AT attitudes, and behaviors among students, staff, and faculty. At both campuses, students had the shortest commute distances and practiced AT more frequently compared with staff and faculty. Geographic locations strongly affected the use of AT and commuters' behaviors and attitudes toward AT. Consistent with TTM predictions, commuters living in towns with adequate university/public transit connectivity to the campuses showed the highest levels of readiness to use AT. Additionally, a strong negative relationship was found between increasing AT stages of change and decreased SOV miles traveled on both campuses (Figure 5), providing some validation of participants' reports of their stage of change. UNH participants rated the cons of AT as significantly lower compared with participants at URI, reflecting the better developed transportation infrastructure at UNH. At both universities, in students, staff, and faculty alike, attitudes and efficacy for AT were strongly related to stage of readiness for AT, consistent with TTM predictions and prior data. The assessment of commute patterns and behaviors shown in this paper is the first step in a program of research that aims to encourage AT behaviors in universities and, ultimately, communities.

Future work will develop and evaluate individual and policy interventions to promote AT based on commute patterns, behavioral models, and geographic information. The study findings should be made known to policy makers, school administrators, and city planners such that they can improve transit infrastructure (e.g., investment, recourse) to maximize its use. For example, new transit investments should be considered first in regions with higher readiness to adopt sustainable transportation.

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# Impacts of Highway Infrastructure Investment Under the American Recovery and Reinvestment Act

**by Seong-Hoon Cho, Daegoon Lee, Dayton M. Lambert, and Roland K. Roberts**

*This study evaluated the impact on highway demand of highway disbursements under the American Recovery and Reinvestment Act (ARRA). Vehicle miles traveled were used to estimate a highway demand equation employing a spatial Durbin model for the 48 contiguous U.S. states during 1994-2008. Estimates from the equation were used to test the hypothesis that highway disbursements caused different upward shifts in the highway demand curves of states. We estimated $8.2 billion in total net benefits for the 48 states as a result of the $27.2 billion in ARRA highway disbursements, yielding an average net benefit of $0.30 per dollar spent.*

## INTRODUCTION

After the United States entered an economic recesssion in December 2007, President Obama signed the American Recovery and Reinvestment Act (ARRA) into law in February 2009 (Romer 2009). The ARRA legislated $787 billion in spending by the federal government under three types of funding programs: $228 billion for tax benefits, $275 billion for contracts, grants and loans, and $224 billion for entitlement spending that included education, unemployment, compensation, food stamps, health care insurance, and other social programs.[1] Spending aimed to create employment oppportunities and save existing jobs (Recovery 2012). The stimulus package focused mainly on saving and creating jobs with ready-to-go (referred to as "shovel-ready") projects that could start straightaway (Berrens et al. 2002; Johnson 2009). Some of the most common shovel-ready projects funded under the ARRA were related to transportation (Rall 2009). Of the $48.1 billion in ARRA funds designated for transportation contracts, grants, and loans, $27.5 billion was allocated to highway infrastructure investment (Recovery 2012).

The ARRA highway disbursement was intended to satisfy increasing demand for highways, recondition aging infrastructure, improve road security and safety, and ease traffic congestion (U.S. Department of Transportation 2012). The highway investment component of the ARRA was particularly important as the U.S. transportation infrastructure has been in need of renovation for many years. Estimates suggest the U.S. economy lost $90 billion in 2010 due to poor transportation infrastructure (American Society of Civil Engineers 2011). The ARRA highway disbursement was expected to improve transportation infrastructure and, thus, mitigate some of the negative economic effects stemming from poor highway conditions.

The objective of this research is to explore the impacts of ARRA highway disbursements, focusing on the cost of the additional highway usage for each of the 48 contiguous states, and the benefits of increased highway usage in each state measured by changes in consumer welfare. The state-level cost-benefit analysis is based on the hypothesis that different levels of ARRA highway disbursements, *ceteris paribus*, shift the state-level demand curves for highway miles upward by different amounts. The hypothesis is premised on the notion that differences in ARRA highway disbursements are expected to improve the quality of state-level highway systems differently (e.g., time saved due to new and expanded facilities, reduced user costs, improved safety, greater passenger comfort, security, convenience and reliability, and/or less damage to goods and freighters).

The hypothesis was tested by estimating a highway demand equation using panel data at the state level for the 1995-2008 period. The price of highway usage was proxied by the sum of the average cost of gasoline ($/mile) and the opportunity cost of travel time ($/mile). Highway demand was represented by vehicle miles traveled (i.e., total number of miles traveled during a year by all vehicles within a state) (U.S. Environmental Protection Agency 2012). *Ex post* simulations of the highway demand equation with and without the ARRA highway disbursement using 2009 and 2010 data generated predicted changes in highway usage for each state. The simulated changes in highway usage were used to estimate changes in consumer welfare from upward shifts in the state-level demand curves, reflecting benefits from the improved quality and quantity of highway systems.

Determining the cost of ARRA highway disbursements requires estimates of both explicit cost (i.e., cost of ARRA highway disbursement) and implicit cost (i.e., cost of negative externalities including air pollution and traffic congestion). While the explicit cost is obtained directly from the government's official website, attaining the implicit cost involves multiple modeling efforts (e.g., contingent valuation of air pollution and estimation of total congestion cost including travel time delays, vehicle operating costs, and social costs of traffic congestion) that are beyond the scope of this research. Thus, the estimates of implicit costs of the additional highway usage due to ARRA higway disbursements were taken directly from previous research.

Our research contributes to the literature in the following way. To the best of our knowledge, our macro-scale cost-benefit analysis of the ARRA highway disbursement at the national and the state levels is the first attempt of its kind. While the literature has firmly established micro-level cost-benefit analysis of highway investment that typically evaluates user benefits and external costs for alternative transportation projects, there appears to be no previous attempt to assess the impact of macro-scale highway investment. For example, Cost-Benefit Analysis (COBA) (Department of Transport, UK 2012), the Micro-computer Benefit Cost Analysis Model (MicroBENCOST) (McFarland et al. 1993), and the Strategic Benefit Cost Analysis Model (StratBENCOST) (National Cooperative Highway Research Program 2004) evaluate the costs and benefits of specific highway improvement projects at the local level.

By estimating state-level highway demand curves for use in evaluating nationwide investment, such as the ARRA highway disbursement, we quantify the benefits of increased highway usage at both the national and the state levels. Using our benefit estimates and the explicit and implicit costs of the ARRA highway disbursement, we estimate the impacts of the ARRA highway disbursement on the aggregate 48 contiguous states and on each state individually. This analysis is meaningful in that the results offer, big picture as well as local impacts of nationwide investment in transportation systems.

## EMPIRICAL MODEL

### Highway Demand Equation

Based on relationships found in the previous literature (Noland 2001; Choo et al. 2004; Small and Van Dender 2005; Washington State Department of Transprotation 2010), highway demand $q$ (measured by vehicle miles traveled) is specified as a function of the price of highway usage $p$ (proxied by the sum of the average cost of gasoline per mile and the cost of travel time per mile), highway disbursements $d$, and other exogenous factors $g$, including the number of licensed drivers to represent the population of highway consumers, per capita income to reflect other socio-economic characteristics, and total highway miles within a state:

(1) $q = f(p, d, g)$

Assuming constant elasticity of demand, we linearize the demand equation by taking natural logarithms of the continuous variables and denote them by capital letters:

(2) $Q_{i,t} = \alpha + \gamma D_{i,t-1} + \mathbf{X}_{i,t}\boldsymbol{\beta} + \mu_i + \lambda_t + \varepsilon_{i,t}$,

where i and t represent the state and year; $\mathbf{X}_{i,t}$ is a 1 × 4 row vector of explanatory variables, including P and G; α and γ are scalar parameters; **β** a 4 × 1 parameter vector; and ε is an error term. Highway disbursements (D) are lagged one year (t-1) because the largest portion of disbursements was for maintanance and capital outlays—land acquistion, design, construction, reconstruction, resurfacing, rehabilitation, installation of guard rails, and fencing—and most of those activities would likely cause some delay in facilitating highway usage. The terms μ and λ, respectively, denote unobserved state-specific and time-specific effects.[2]

The equation (2) intrinsically involves a spatial network system because the highway vehicle miles of states located near one another may have unobserved characteristics that are correlated across states. These unobserved characteristics represent the spatial autocorrelation of the highway demand as an unobserved spatial process. For example, there may be spatial spillover impacts on vehicle miles traveled in states neighboring the states where the funds were disbursed. We take account of the spatial spillover impacts by framing the highway deamand equation in a spatial regression model that accounts for such spatial dependence (LeSage and Pace 2009; Parent and LeSage 2010). Inclusion of the spatially lagged depdendent variable assumes that highway demand in one location is codetermined by demand for highways in neighboring regions.

Following a routine suggested by Elhorst (2010), we tested the non-spatial highway demand equation against the corresponding spatial model. We specified the highway demand equation as a spatial Durbin model for panel data (SDMP) that include both spatial lag, error, and cross-regressive structures (Anselin 1988; LeSage and Pace 2009):

(3) $Q_{i,t} = \rho\sum_{j=1}^{N} w_{ij}Q_{j,t} + \alpha + \gamma D_{i,t-1} + \psi\sum_{j=1}^{N} w_{ij}D_{j,t-1} + \mathbf{X}_{i,t}\boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij}\mathbf{X}_{j,t}\boldsymbol{\Phi} + \mu_i + \lambda_t + \varepsilon_{i,t}$

where subscripts *i* and *j* represent the *i*th and *j*th states, $w_{ij}$ is element $(i, j)$ of the $N \times N$ spatial weight matrix $W$ whose diagonal elements are zero $\sum_{j=1}^{N} w_{ij}Q_{j,t}$, is annual vehicle miles traveled within the

neighbors defined by the spatial weight matrix $W$, $\rho$ is a parameter of spatially lagged annual vehicle miles, $\psi$ is a parameter of spatially lagged highway disbursement, and Φ is a 4 × 1 parameter vector of spatially lagged independent variables. We estimated the highway demand equation with a fixed effect model allowing for arbitrary correlation between the 48 contiguous U.S. states' heterogeneity and other explanatory variables. The lag AR term ρ explains this dependence. If the covariates are measured with error, and those measurement errors are correlated across spatial units, then inclusion of the error correlation term is warranted. If level effects of neighboring covariates determine highway expenditures, then the cross-regressive terms are important. These hypotheses can be tested to determine if the SDM, or some nested version of the SDM model, is suitable.

**Estimation Procedure**

Based on the specification results and the panel data model discussed above, the highway demand equation was estimated by maximum likelihood.[3] In the spatial regression model, interpretation of the estimates, i.e., β and Φ, is not straightforward because spatial spillover effects play signficant roles in determining the marginal effects of the variables (LeSage and Pace 2009). Applying the approach by LeSage and Pace (2009), the total marginal effect of a change in an explanatory variable in state *i* on vehicle miles traveled in the 48 U.S. states was decomposed into the effect on vehicle miles traveled in state *i* as a direct marginal effect (hereafter referred to as direct effect) and the effect on vehicle miles traveled outside state *i* as an indirect marginal effect (hereafter, referred to as indirect

effect).[4] The direct effect refers to the combination of (1) the effect of an explanatory variable for the *i*th state on vehicle miles traveled in the *i*th state and (2) the effect passing through neighboring regions that exert a feedback influence on vehicle miles traveled of the *i*th state (referred to as "feedback effect"). The indirect effect refers to the sum of the effects of an explanatory variable for the *i*th state on vehicle miles traveled in the other states (-*i*). The total effect is the sum of the direct and indirect effects, which denote the effect of a one-unit change in an explanatory variable on the aggregate vehicle miles traveled in all 48 states.

**Cost-benefit Analysis With and Without ARRA Highway Disbursement**

Using the parameter estimates from Equation (3), the highway demand curves for vehicle miles traveled in state *i* 1) in the absence of ARRA highway disbursements to any of the 48 states ($Q_i^{wo}$), 2) with the ARRA diburseme to state *i* only ($Q_i^{own}$), and 3) with the ARRA distbursements to each of the 48 states ($Q_i^{all}$) are:

$$\text{(4-1)}\quad Q_i^{wo} = \left[(I-\hat{\rho}W)^{-1}\boldsymbol{i}_i\right]'(\hat{\alpha}\boldsymbol{i}_N + \hat{\gamma}D^{wo} + \hat{\chi}WD^{wo} + \mathbf{X}\hat{\boldsymbol{\beta}} + W\mathbf{X}\hat{\boldsymbol{\Phi}} + \hat{\mu}),$$

$$\text{(4-2)}\quad Q_i^{own} = \left[(I-\hat{\rho}W)^{-1}\boldsymbol{i}_i\right]'(\hat{\alpha}\boldsymbol{i}_N + \hat{\gamma}D^{own,i} + \hat{\chi}WD^{own,i} + \mathbf{X}\hat{\boldsymbol{\beta}} + W\mathbf{X}\hat{\boldsymbol{\Phi}} + \hat{\mu}),$$

$$\text{(4-3)}\quad Q_i^{all} = \left[(I-\hat{\rho}W)^{-1}\boldsymbol{i}_i\right]'(\hat{\alpha}\boldsymbol{i}_N + \hat{\gamma}D^{all} + \hat{\chi}WD^{all} + \mathbf{X}\hat{\boldsymbol{\beta}} + W\mathbf{X}\hat{\boldsymbol{\Phi}} + \hat{\mu}),$$

where *wo* denotes without ARRA disbursements to any state, *own* represents the case where only state *i* receives its ARRA disbursement with all other states not being funded, *all* represents the case where all 48 states receive their ARRA disbursements, *i* indexes states, *D* is highway disbursements in 2009, **X** is a matrix of explanatory variables (i.e., the price of highway usage, per capita income, length of highway, and number of licensed drivers) in 2010, and $\boldsymbol{i}_i$ is an $N$ by 1 unit vector with the $i^{th}$ element being 1 and the other elements being 0. Note that we obtain 48 different predicted values for equation (4-2) since $D^{own,i}$ varies by $i = 1,\ldots,48$. Equation (4-2) is constructed to see what would have been the effect of ARRA disbursement in a state if only that state had been funded with ARRA disbursement. While comparing the predicted values from equations (4-3) and (4-1) shows the total effect of ARRA disbursements on highway demand, comparing those from equations (4-3) and (4-2) shows the portion of the total effect resulting from spillovers. Intuitively, the difference between the predicted values from (4-3) and (4-2) is the effect of other states' ARRA disbursements on state *i*'s demand for highway use.

Once predicted vehicle miles traveled are obtained, we draw three different constant-elasticity demand curves for each state. The inverse demand curves for each of the 48 states are $p_i = k_i^{wo} q_i^{\eta_i}$, $p_i = k_i^{own} q_i^{\eta_i}$ and $p_i = k_i^{all} q_i^{\eta_i}$, where $k_i^{wo}$, $k_i^{own}$, and $k_i^{all}$ denote all factors including ARRA disbursements that shift the demand curves of state *i* (referred to as "demand curve shifter"), and $\eta_i^{wo}, \eta_i^{own}$ and $\eta_i^{all}$ are price flexibilities (inverse price elasticities).

An important question deals with which value is an appropriate estimate for the price elasticity. As pointed out in the section Estimation Procedure, the parameter estimate for the price elasticity $\beta_p$ is not the marginal effect because it does not reflect spatial iterations. The total effect includes the indirect effect, which by definition represents changes in demand caused by price changes in neighboring states. Because highway use in neighboring states is either a substitute or complement to one's own state highway use, a price change in neighboring states shifts the one's own state demand curve rather than changing its price elasticity of demand.

Hypothetical highway demand curves corresponding to, $q_i^{wo}, q_i^{own}$, and $q_i^{all}$ are shown in Figure 1. The relationships among the demand curves, $q_i^{wo} < q_i^{own}$, $q_i^{wo} < q_i^{all}$, and $q_i^{own} < q_i^{all}$ are hypothesized because we expect ARRA highway disbursements to shift the demand curve for state *i* to the right,

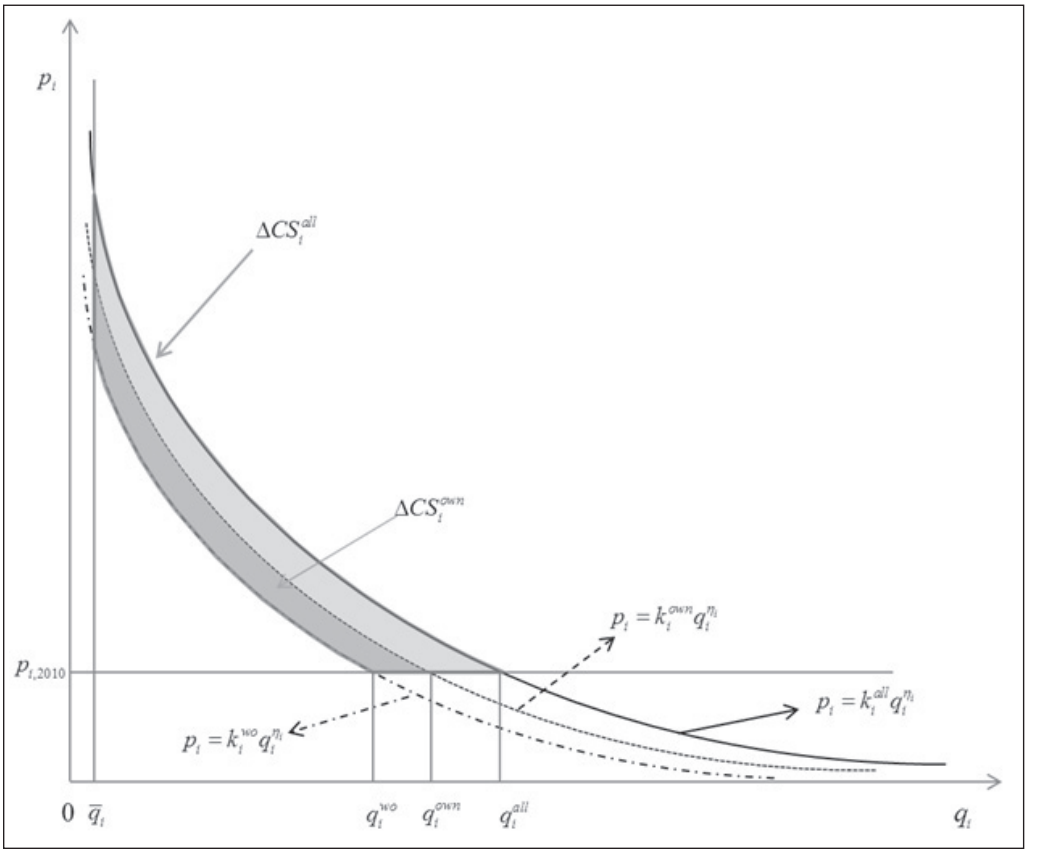
and the vehicle miles traveled with ARRA highway disbursement in all 48 states are expected to increase more than in a given state because of positive spillover effects.

Given the estimated highway demand curves, the benefits of increased vehicle miles traveled for each state due to the ARRA highway disbursement in a given state and in all 48 states were estimated by calculating the additional consumer surplus attributed to the right shifts in the highway demand curves in a state and in all 48 states (shown as $\Delta CS_i^{own}$ and $\Delta CS_i^{all}$ in Figure 1). The additional consumer surplus due to the ARRA highway disbursements in all 48 states was calculated by integrating the area $\Delta CS_i^{all}$:

$$\begin{aligned}\Delta CS_i^{all} &= \left[\int_{\overline{q}}^{q_i^{all}} (k_i^{all} q_i^{\eta_i}) dq_i - p_{i,2010}(q_i^{all} - \overline{q}_i)\right] - \left[\int_{\overline{q}}^{q_i^{wo}} (k_i^{wo} q_i^{\eta_i}) dq_i - p_{i,2010}(q_i^{wo} - \overline{q}_i)\right] \\ &= \left[\frac{k_i^{all}}{\eta_i + 1}\left\{(q_i^{all})^{\eta_i+1} - (\overline{q})^{\eta_i+1}\right\} - p_{i,2010}(q_i^{all} - \overline{q}_i)\right] - \left[\frac{k_i^{wo}}{\eta_i + 1}\left\{(q_i^{wo})^{\eta_i+1} - (\overline{q})^{\eta_i+1}\right\} - p_{i,2010}(q_i^{wo} - \overline{q}_i)\right],\end{aligned} \tag{5}$$

where $\overline{q}_i$ is an arbitrarily chosen but reasonably low cutoff value (i.e., vehicle miles traveled corresponding to a price ceiling of 100 times $p_{i,2010}$ in the inverse demand curve $p_i = k_i^{wo} q_i^{\eta_i}$). The area $\Delta CS_i^{own}$ was calculated likewise. The decomposition of $\Delta CS_i^{all}$ into $\Delta CS_i^{own}$, and $(\Delta CS_i^{all} - \Delta CS_i^{own})$ is meaningful because $\Delta CS_i^{own}$ measures the additional consumer surplus in a given state related to the ARRA highway disbursement in that state, while it measures the additional consumer surplus in the given state related to the ARRA highway disbursements in the other states (referred to as "spillover consumer welfare").

**Figure 1: Estimated Demand Curves Without and With ARRA Highway Disbursement in a Given State and in All 48 States**



The difference between the predicted vehicle miles traveled with and without ARRA highway disbursements in all 48 states ($q_i^{all} - q_i^{wo}$) was multiplied by $0.09 per mile (taken directly from Litman and Doherty (2009)—see details in the Study Area and Data section) to calculate the additional implicit cost of negative externalities. Subsequently, the total net benefit for each state from the ARRA highway disbursements was calculated by subtracting the sum of explicit and implicit costs from total additional consumer surplus. The net benefits were aggregated across states to arrive at the total net benefit from ARRA highway disbursements to the 48 contiguous states.

## STUDY AREA AND DATA

The cross-sectional data used to estimate the highway demand curves pertain to the 48 contiguous U.S. states for 15 years (1994-2008). Similar cross-sectional data for 2009's ARRA highway disbursements and the other explanatory variables for 2010 were used to simulate the impact of time-lagged ARRA highway disbursements on highway demand in 2010. Data for the 2009 ARRA highway disbursements by state were obtained from www.recovery.gov, the U.S. government's official website (Recovery 2012). The annual retail price of gasoline was obtained from the U.S. Energy Information Administration (U.S. Energy Information Agency 2012); per capita income was collected from the U.S. Department of Commerce, Bureau of Economic Analysis (USDC BEA 2012); and vehicle miles traveled, highway disbursements, length of highways, number of licensed drivers, and fuel tax per gallon were obtained from the Highway Statistics series published by the U.S. Department of Transportation, Federal Highway Administration (USDOT FHWA 2012). Although ARRA disbusements by state were available for 2009, highway disbursements by state were not available for that year. Thus, highway disbursements by state in the absence of the 2009 ARRA disbursements were predicted by each state's time trend using highway disbursement data from 1994 to 2008.

The average opportunity cost of travel time per mile in the United Sates (i.e., $0.11 per mile) was obtained from Litman and Doherty (2009), as was the per-mile cost of congestion, which was estimated as a weighted average of congestion levels for urban peak, off-peak, and rural areas, multiplied by weighted hourly wages.

The cost of negative externalities from air pollution and traffic congestion (i.e., $0.09 per mile) (Litman and Doherty 2009) was estimated by summing $0.04 for the non-greenhouse gas air pollution cost, $0.02 for the greenhouse gas cost, and $0.03 for the congestion cost, all per-average vehicle mile traveled. All data, except travel time cost and the costs of negative externalities, were obtained at the state level and all dollar values (i.e., gasoline price, travel time cost, highway disbursements, and per-capita income) were adjusted to 2007 dollars using the consumer price index (U.S. Department of Labor, Bureau of Labor Statistics 2012). Definitions of the variables used in the regressions and descriptive statistics are reported in Table 1.

Annual vehicle miles traveled for each state were used to represent highway demand. The vehicle miles traveled in the United States steadily increased from 2,342 billion miles in 1994 to 2,955 billion miles in 2008 (a 26% increase), with the exception of a slight drop in 2008 during the recession. As shown in Figure 2a, California and Texas stand out as the states with the most vehicle miles traveled during 1994-2008, with 307 and 215 billion miles, respectively, while Delaware, North Dakota, Rhode Island, South Dakota, Vermont, Wyoming, Montana, New Hampshire, and Idaho had the fewest vehicle miles traveled with fewer than 10 billion miles traveled (see Table 2).

The per-mile retail price of gasoline, state-level fuel tax, and opportunity cost of travel time were summed to represent the price of a vehicle mile traveled.[5] The retail price of gasoline has varied across states with a range of around 10% between the highest and the lowest prices. The West Coast and New England are in the higher price range while the Midwest is in the lower price range (see Figure 2b). Over the 15 years, average real gasoline prices for individual states have increased

**Table 1: Variable Names, Descriptions, and Descriptive Statistics**

| Variable† | Description | Mean | Std Dev |
|---|---|---|---|
| Vehicle miles traveled (1995-2008) | Annual vehicle distance traveled by all vehicles (billion miles) | 57.731 | 57.023 |
| Highway disbursement (1994-2007) | Total disbursement for highways from all units of government ($ billion) | 2.644 | 2.309 |
| Price (1995-2008) | Sum of gasoline price and opportunity cost of travel time ($/mile) | 0.200 | 0.012 |
| Per capita income (1995-2008) | Per capita income ($ thousand) | 34.608 | 5.547 |
| Length of highway (1995-2008) | Total highway length (thousand mile) | 82.174 | 50.978 |
| Licensed drivers (1995-2008) | Total number of licensed drivers (million) | 3.984 | 4.057 |

† All values are across states and across years.

**Figure 2a: Average Vehicle Miles Traveled During 1994-2008 (million miles)**

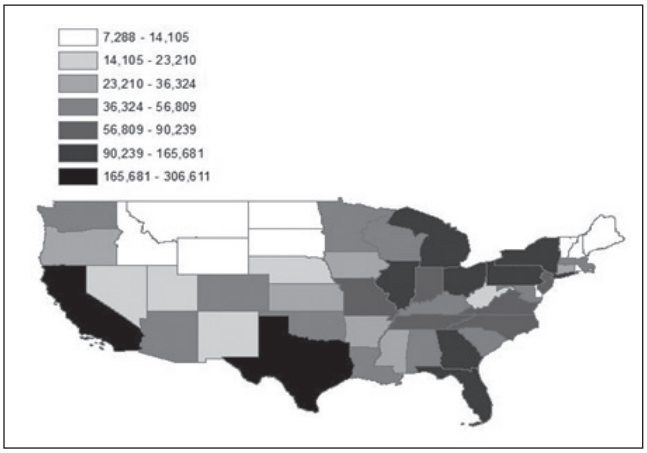
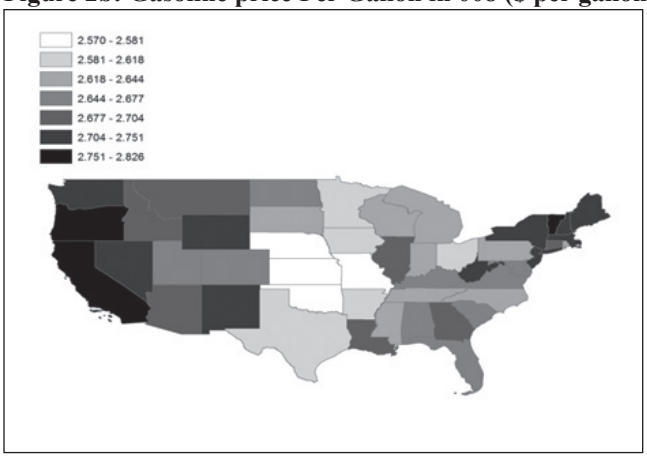



**Figure 2b: Gasoline price Per Gallon in 008 ($ per gallon)**



between 131% and 179% (U.S. Energy Information Agency 2012). Fuel taxes that add to the price of gasoline differed in 2008 from $0.36 per gallon in West Virginia to $0.08 per gallon in Georgia.

In the estimation, highway disbursement is total investment in highways by federal, state, and local governments (e.g., capital outlay, maintenance and services, administration, and research and planning). Between 1994 and 2008, highway disbursement in 2007 dollars increased by 50% from $88 billion to $132 billion for the aggregate 48 states. Highway disbursements were highest in California, Texas, and New York (over $6 billion per year) on average over the 15 years, while Vermont, Rhode Island, and North Dakota had the lowest highway disbursements (less than $0.4 billion per year). The allocation among states of the $27 billion in ARRA highway disbursement amounted to between 12.6% and 47.5% of each state's highway disbursement in 2008. Correlation between state highway disbursements in 2008 and state ARRA highway disbursements was 0.96, indicating that the share of the total ARRA disbursement was distributed according to each state's existing share of highway disbursement (see Figures 3a and 3b for the distribution of highway disbursement in 2008 and ARRA highway disbursement, respectively).

**Figure 3a: Highway Disbursement in 2008 ($ million)**

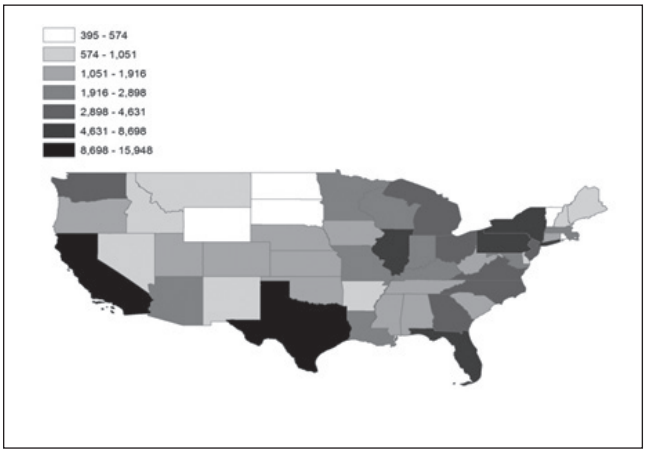



**Figure 3b: ARRA Highway Disbursement in 2009 ($ million)**

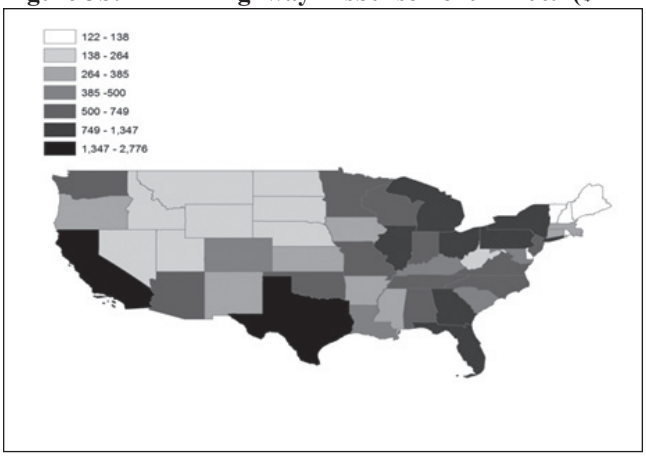


**Table 2: Average Vehicle Miles Traveled During 1994-2008, Gasoline Price Per Gallon in 2008, Highway Disbursement in 2008, ARRA Highway Disbursement in 2009**

| | Average vehicle miles travelled during 1994-2008 (million miles) | Gasoline price per gallon in 2008 ($ per gallon) | Highway disbursement in 2008 ($ million) | ARRA highway disbursement in 2009 ($ million) |
|---|---|---|---|---|
| Alabama | 56,342 | 2.669503 | 1,916 | 620 |
| Arizona | 50,961 | 2.681059 | 2,806 | 585 |
| Arkansas | 29,824 | 2.605943 | 1,051 | 367 |
| California | 306,611 | 2.80529 | 14,697 | 2,776 |
| Colorado | 42,225 | 2.665651 | 1,695 | 445 |
| Connecticut | 30,278 | 2.704172 | 1,370 | 300 |
| Delaware | 8,559 | 2.652169 | 683 | 122 |
| Florida | 165,681 | 2.664688 | 8,698 | 1,347 |
| Georgia | 102,556 | 2.69069 | 3,817 | 904 |
| Idaho | 13,939 | 2.703209 | 802 | 194 |
| Illinois | 102,733 | 2.688764 | 6,299 | 939 |
| Indiana | 69,706 | 2.629056 | 2,732 | 657 |
| Iowa | 29,464 | 2.618463 | 1,505 | 358 |
| Kansas | 27,952 | 2.57609 | 1,487 | 349 |
| Kentucky | 45,543 | 2.666614 | 2,404 | 448 |
| Louisiana | 42,046 | 2.684911 | 2,488 | 435 |
| Maine | 14,105 | 2.740767 | 739 | 138 |
| Maryland | 51,291 | 2.657947 | 2,747 | 447 |
| Massachusetts | 52,456 | 2.717654 | 2,898 | 385 |
| Michigan | 97,176 | 2.632908 | 3,269 | 896 |
| Minnesota | 52,200 | 2.598239 | 2,352 | 557 |
| Mississippi | 36,324 | 2.626167 | 1,346 | 355 |
| Missouri | 65,806 | 2.572238 | 2,545 | 640 |
| Montana | 10,244 | 2.698394 | 651 | 264 |
| Nebraska | 18,037 | 2.570312 | 1,352 | 230 |
| Nevada | 18,084 | 2.725358 | 906 | 221 |
| New Hampshire | 12,243 | 2.713802 | 681 | 130 |
| New Jersey | 68,290 | 2.71958 | 3,921 | 679 |
| New Mexico | 23,210 | 2.716691 | 860 | 306 |
| New York | 128,855 | 2.723432 | 7,537 | 957 |
| North Carolina | 90,239 | 2.643501 | 3,584 | 744 |
| North Dakota | 7,288 | 2.677207 | 471 | 184 |
| Ohio | 106,521 | 2.59535 | 4,631 | 936 |
| Oklahoma | 43,736 | 2.580905 | 1,634 | 565 |
| Oregon | 33,508 | 2.825513 | 1,364 | 300 |
| Pennsylvania | 102,703 | 2.642538 | 5,956 | 1,035 |
| Rhode Island | 7,947 | 2.629056 | 419 | 137 |
| South Carolina | 45,431 | 2.665651 | 1,470 | 500 |
| South Dakota | 8,382 | 2.632908 | 451 | 214 |
| Tennessee | 65,384 | 2.640612 | 1,771 | 749 |
| Texas | 214,964 | 2.612685 | 15,948 | 2,263 |
| Utah | 22,895 | 2.675281 | 1,229 | 224 |
| Vermont | 7,411 | 2.820698 | 395 | 129 |
| Virginia | 75,544 | 2.659873 | 3,875 | 691 |
| Washington | 53,249 | 2.75136 | 3,901 | 578 |
| West Virginia | 19,356 | 2.721506 | 1,208 | 212 |
| Wisconsin | 56,809 | 2.642538 | 2,392 | 562 |
| Wyoming | 8,398 | 2.730174 | 574 | 185 |

Average vehicle miles traveled in 1994-2008 and highway disbursement in 2008 from USDOT-FHWA (2012) Gasoline price per gallon in 2008 from U.S. Energy Information Agency (2012). ARRA highway disbursement in 2009 from Recovery (2012).

## EMPIRICAL RESULTS

### Regression Results

The parameter estimates and direct, indirect, and total effects of the SDMP are shown in Table 3. The positive and significant spatial lag parameter (ρ) suggests a spatial spillover effect of vehicle miles traveled, which is consistent with the results of the spatial LM, Wald, and LR tests discussed in the Empirical Model section. Specifically, a 1% increase in vehicle miles traveled in the neighbors yielded a 0.20% increase in the own state's vehicle miles traveled on average.

**Table 3: Regression Results of the SDMP Model with Spatial-Fixed Effects and Neighbors Defined by *HW1***

| Variables | Parameter estimates | Direct effects | Indirect effects | Total effects |
|---|---|---|---|---|
| Intercept | 2.132* | | | |
| | (0.842) | | | |
| ln (Highway disbursement), *t*-1 | 0.028* | 0.029* | 0.031 | 0.060* |
| | (0.008) | (0.008) | (0.019) | (0.021) |
| ln (Price) | -0.997* | -0.957* | 0.763* | -0.194* |
| | (0.227) | (0.220) | (0.227) | (0.034) |
| ln (Per capita income) | 0.252* | 0.257* | 0.160 | 0.417* |
| | (0.060) | (0.058) | (0.075) | (0.054) |
| ln (Length of highway) | 0.026 | 0.041 | 0.331* | 0.372* |
| | (0.039) | (0.038) | (0.061) | (0.066) |
| ln (Licensed drivers) | 0.302* | 0.324* | 0.466* | 0.790* |
| | (0.038) | (0.037) | (0.069) | (0.072) |
| *HW1**ln (Highway disbursement), *t*-1 | 0.020 | | | |
| | (0.016) | | | |
| *HW1**ln (Price) | 0.841* | | | |
| | (0.229) | | | |
| *HW1**ln (Per capita income) | 0.082 | | | |
| | (0.076) | | | |
| *HW1**ln (Length of highway) | 0.272* | | | |
| | (0.051) | | | |
| *HW1**ln (Licensed drivers) | 0.328* | | | |
| | (0.064) | | | |
| *HW1**ln (Vehicle miles travelled), $\rho$ | 0.201* | | | |
| | (0.048) | | | |
| Adjusted $R^2$ | 0.8277 | | | |

*Denotes $\rho < 0.05$

All non-lagged explanatory variables except the length of highway are significant. The signs of all the significant variables are in agreement with expectations, which shows that the states with higher highway disbursements, per capita incomes, and numbers of licensed drivers tend to use highways more. The spatially lagged explanatory variables that are positive and significant (i.e., price, length of highway, and number of licensed drivers) reflect positive spatial spillover effects on vehicle miles traveled.

An increase by 1% in a state's one-year lagged highway disbursement increases vehicle miles traveled inside the state by 0.03% and across all states by 0.06%. These results suggest that government investment in highways perhaps enhances either the quantity or quality (or both) of highways and thus increases highway usage. The larger total effect than direct effect of the highway disbursement suggests that a state-level shock in highway disbursement has an even larger effect on demand for the regional highway network. The results explicitly predict that the 2009 ARRA highway disbursement increased highway usage.

The price per mile has direct, indirect, and total effects on vehicle miles of -0.96, 0.76, and -0.19, respectively. These results suggest that the positive indirect effect moderated the close-to-unit-elastic demand for highway usage to yield an inelastic regional highway demand based on the total effect. The positive indirect effect suggests that an increase in the price of highway usage in a state increases vehicle miles traveled in other states. This finding implies that highway usage in one state is a substitute for highway usage in neighboring states.

The direct and total effects of per capita income on vehicle miles traveled suggest that a 1% increase in per-capita income in a state increased vehicle miles traveled by 0.26% and 0.42% in the state and the regional highway systems, respectively. These findings suggest that highway usage is a necessity, implying that highway usage does not decrease appreciably during economically tough times.

The indirect and total effects of highway length are both positive and significant. These results suggest that a 1% increase in highway length in a state increased vehicle miles traveled outside of the state and in all 48 states by 0.33% and 0.37%, respectively. These results imply that an increase in highway miles within a state increased the accessibility of the highways in neighboring states, inducing greater highway use in those states, resulting in an increase in regional highway demand.

The direct, indirect, and total effects of the number of licensed drivers are all positive and significant. This variable plays a crucial role in the regression to control for the effects on vehicle miles traveled of the large variation in population size across states. The estimates suggest that a 1% increase in the number of licensed drivers in a state increased highway usages in the state, outside the state, and in the regional highway system by 0.32%, 0.47% and 0.79%, respectively. The higher indirect effect than the direct effect implies a greater effect on vehicle miles traveled in other states than within the state.

**Simulation Results**

The predicted effects of the 2009 ARRA highway disbursement on vehicle miles traveled, consumer surplus, costs, and net benefits in 2010 are presented in Table 4. Results suggest that the ARRA highway disbursement increased vehicle miles traveled in the 48 states by 36 billion miles, which amounts to a 1.2% increase (i.e., final row of the ($q_i^{all} - q_i^{wo}$) column in Table 4). In each state, the predicted increase in vehicle miles traveled with the ARRA highway disbursement (see "($q_i^{all} - q_i^{wo}$)" column in Table 4) is greater than the predicted increase with state *i*'s own disbursement alone (see "($q_i^{all} - q_i^{wo}$)" column in Table 4), i.e., $q_i^{wo} < q_i^{own} < q_i^{all}$. The findings support the hypotheses that the ARRA highway disbursement shifted the demand curve for highway use upward, and vehicle miles traveled in a state increased more when the ARRA highway disbursement was distributed throughout all states than if its distribution were limited within that state because of the positive spillover effect.

The increase in vehicle miles traveled in a given state, resulting from that state's ARRA highway disbursement (see "($q_i^{all} - q_i^{wo}$)" column in Table 4), ranged from 38 million miles for Delaware to 1.99 billion miles for California, whereas increases in vehicle miles traveled in a given state with the ARRA highway disbursement distributed throughout all states (see "($q_i^{all} - q_i^{wo}$)" column in Table 4) ranged from 78 million miles or Delaware to 3.83 billion miles for California. These increases in vehicle miles traveled generated additional consumer surplus between \$43 million for Delaware and \$2.22 billion for California (see "$\Delta CS_i^{own}$" column in Table 4) when the ARRA disbursement was for a given state, and between \$87 million and \$4.27 billion (see "$\Delta CS^{all}$" column in Table 4) when the ARRA disbursements were distributed to all states. Given the implicit costs of negative externalities by state between \$7 million and \$337 million (see "Implicit cost" column in Table 4) and explicit costs of between \$122 million and \$2.78 billion (see "Explicit cost" column in Table 4), total net benefits ranged from –\$132 million for New Jersey to \$1,158 million for California, which summed to \$8.24 billion over the 48 states (see "Total net benefit" column in Table 4). As a result, the net benefit per dollar spent ranged from –\$0.34 for Delaware to

**Table 4: Costs and Benefits of ARRA Highway Disbursement**

| States | Own | | Total | | Spillover consumer welfare | Implicit cost (Negative externality) ($ million) | Explicit cost ($ million) | Total net benefit | Net benefit per dollar spent ($) |
|---|---|---|---|---|---|---|---|---|---|
| | $q_i^{own} - q_i^{wo}$ (million mile) | $\Delta CS_i^{own}$ ($ million) | $q_i^{all} - q_i^{wo}$ (million mile) | $\Delta CS_i^{all}$ ($ million) | $\Delta CS_i^{all} - \Delta CS_i^{own}$ ($ million) | | | ($\Delta CS_i^{all}$ – Implicit cost – Explicit cost) ($ million) | |
| Alabama | 536 | 565 | 1,004 | 1,058 | 493 | 88 | 620 | 349 | 0.56 |
| Arizona | 314 | 348 | 656 | 727 | 379 | 58 | 585 | 84 | 0.14 |
| Arkansas | 258 | 271 | 486 | 509 | 238 | 43 | 367 | 100 | 0.27 |
| California | 1,986 | 2,217 | 3,826 | 4,271 | 2,054 | 337 | 2,776 | 1,158 | 0.42 |
| Colorado | 300 | 320 | 619 | 660 | 340 | 54 | 445 | 161 | 0.36 |
| Connecticut | 182 | 200 | 356 | 392 | 192 | 31 | 300 | 60 | 0.20 |
| Delaware | 38 | 43 | 78 | 87 | 45 | 7 | 122 | -41 | -0.34 |
| Florida | 800 | 833 | 2,321 | 2,419 | 1,586 | 204 | 1,347 | 868 | 0.64 |
| Georgia | 929 | 988 | 1,747 | 1,859 | 871 | 154 | 904 | 801 | 0.89 |
| Idaho | 110 | 120 | 211 | 229 | 110 | 19 | 194 | 17 | 0.09 |
| Illinois | 523 | 554 | 1,208 | 1,279 | 725 | 106 | 939 | 234 | 0.25 |
| Indiana | 458 | 486 | 880 | 933 | 447 | 77 | 657 | 198 | 0.30 |
| Iowa | 193 | 204 | 397 | 420 | 216 | 35 | 358 | 27 | 0.08 |
| Kansas | 171 | 182 | 370 | 394 | 212 | 33 | 349 | 12 | 0.04 |
| Kentucky | 273 | 290 | 591 | 628 | 338 | 52 | 448 | 129 | 0.29 |
| Louisiana | 284 | 299 | 607 | 639 | 339 | 53 | 435 | 150 | 0.35 |
| Maine | 80 | 87 | 170 | 185 | 98 | 15 | 138 | 31 | 0.23 |
| Maryland | 287 | 317 | 532 | 588 | 271 | 47 | 447 | 94 | 0.21 |
| Massachusetts | 186 | 209 | 546 | 612 | 403 | 48 | 385 | 179 | 0.47 |
| Michigan | 677 | 714 | 1,256 | 1,325 | 611 | 111 | 896 | 319 | 0.36 |
| Minnesota | 361 | 384 | 795 | 848 | 463 | 70 | 557 | 220 | 0.40 |
| Mississippi | 274 | 291 | 584 | 621 | 329 | 51 | 355 | 214 | 0.60 |
| Missouri | 411 | 430 | 884 | 925 | 495 | 78 | 640 | 207 | 0.32 |
| Montana | 109 | 117 | 207 | 222 | 105 | 18 | 264 | -60 | -0.23 |
| Nebraska | 104 | 112 | 252 | 269 | 158 | 22 | 230 | 17 | 0.08 |

**Table 4: continued**

| States | Own | | Total | | Spillover consumer welfare | Implicit cost (Negative externality) ($ million) | Explicit cost ($ million) | Total net benefit ($\Delta CS_i^{all}$ – Implicit cost – Explicit cost) ($ million) | Net benefit per dollar spent ($) |
|---|---|---|---|---|---|---|---|---|---|
| | $q_i^{own} - q_i^{wo}$ (million mile) | $\Delta CS_i^{own}$ ($ million) | $q_i^{all} - q_i^{wo}$ (million mile) | $\Delta CS_i^{all}$ ($ million) | $\Delta CS_i^{all} - \Delta CS_i^{own}$ ($ million) | | | | |
| Nevada | 112 | 128 | 224 | 255 | 127 | 20 | 221 | 15 | 0.07 |
| New Hampshire | 80 | 91 | 157 | 178 | 87 | 14 | 130 | 35 | 0.27 |
| New Jersey | 253 | 270 | 558 | 595 | 325 | 49 | 679 | -132 | -0.19 |
| New Mexico | 203 | 211 | 365 | 380 | 169 | 32 | 306 | 41 | 0.13 |
| New York | 467 | 501 | 1,232 | 1,323 | 822 | 108 | 957 | 258 | 0.27 |
| North Carolina | 533 | 587 | 1,235 | 1,359 | 772 | 109 | 744 | 506 | 0.68 |
| North Dakota | 80 | 85 | 153 | 163 | 78 | 13 | 184 | -35 | -0.19 |
| Ohio | 618 | 662 | 1,210 | 1,296 | 634 | 106 | 936 | 253 | 0.27 |
| Oklahoma | 406 | 429 | 698 | 738 | 309 | 61 | 565 | 111 | 0.20 |
| Oregon | 206 | 236 | 410 | 472 | 235 | 36 | 300 | 136 | 0.45 |
| Pennsylvania | 515 | 563 | 974 | 1,064 | 501 | 86 | 1,035 | -56 | -0.05 |
| Rhode Island | 70 | 79 | 102 | 116 | 37 | 9 | 137 | -31 | -0.22 |
| South Carolina | 432 | 463 | 764 | 820 | 357 | 67 | 500 | 253 | 0.51 |
| South Dakota | 102 | 109 | 169 | 181 | 72 | 15 | 214 | -48 | -0.22 |
| Tennessee | 732 | 773 | 1,187 | 1,254 | 481 | 104 | 749 | 400 | 0.53 |
| Texas | 1,200 | 1,245 | 3,005 | 3,117 | 1,872 | 264 | 2,263 | 590 | 0.26 |
| Utah | 113 | 121 | 287 | 308 | 187 | 25 | 224 | 58 | 0.26 |
| Vermont | 70 | 78 | 106 | 117 | 39 | 9 | 129 | -22 | -0.17 |
| Virginia | 425 | 452 | 874 | 930 | 477 | 77 | 691 | 162 | 0.23 |
| Washington | 282 | 326 | 621 | 720 | 393 | 55 | 578 | 87 | 0.15 |
| West Virginia | 92 | 100 | 196 | 212 | 113 | 17 | 212 | -17 | -0.08 |
| Wisconsin | 375 | 406 | 742 | 805 | 398 | 65 | 562 | 177 | 0.31 |
| Wyoming | 86 | 91 | 155 | 163 | 72 | 14 | 185 | -36 | -0.19 |
| Sum over the 48 states | 17,295 | 18,589 | 36,005 | 38,664 | 20,076 | 3,168 | 27,257 | 8,239 | 0.30 |

$0.89 for Georgia, with a weighted average net benefit of $0.30 per dollar spent across the 48 states (see "Net benefit per dollar spent" column in Table 4).

The total increase in vehicle miles traveled for the 48 states $\left(\sum_{i=1}^{48}\left(q_i^{all} - q_i^{wo}\right)\right)$ of 36.01 billion miles generated $38.66 billion in additional consumer surplus $\left(\sum_{i=1}^{48}\Delta CS_i^{all}\right)$. About 50% is attributed to benefits received by states other than the one receiving the ARRA disbursement i.e., 17.30 billion miles generated $18.59 billion in additional consumer surplus $(\Delta CS_i^{all} - \Delta CS_i^{own})$. The considerable differences between the increases in predicted vehicle miles traveled in a given state from the ARRA disbursement in that state and the predicted vehicle miles traveled when the ARRA disbursement is made to all 48 states imply the ARRA highway disbursement had a sizable spatial spillover impact on highway demand.

## CONCLUSIONS

This study evaluated the impact of the 2009 ARRA highway disbursement on vehicle miles traveled, reflecting a shift in highway demand, in the framework of a cost-benefit analysis. We estimated a highway demand equation that employed SDMP based on panel data pertaining to the 48 U.S. contiguous states for the 1994-2008 period. The estimates from the equation supported the hypothesis that different state-level ARRA highway disbursements resulted in different upward shifts in the highway demand curves across states. The different effects on the state-level demand curves resulted in increases in vehicle miles traveled that were different for each state, generating a wide range of predicted increases in consumer surplus across states. The estimated figures and explicit and implicit costs associated with the additional highway usage were used to estimate total net benefit and net benefit per dollar spent for each state and for the 48 states. Our estimates found a total net benefit of $8.2 billion summed across the 48 states resulting from the $27.2 billion 2009 ARRA highway disbursement, which yielded a weighted average of $0.30 in net benefits per dollar spent.

Besides the core finding of a positive net benefit of the ARRA highway disbursement, another key finding is that about half of the increased vehicle miles traveled resulting from the ARRA highway disbursement was due to the spatial spillover impacts on vehicle miles traveled in states neighboring the states where the funds were disbursed. This result implies that about half the benefits from improving a state's highway system are disseminated outside the state to the users of multistate highway networks.

The approach used in this study does not address the question about whether the ARRA was beneficial in rehabilitating the deeply depressed economy. However, given the assumptions of the SDMP and the e*x post* simulated welfare calculations, our estimates suggest a positive national net benefit from the ARRA disbursement emanating from increased highway demand.

Another implication of this study is that the dollar value of the ARRA highway disbursement is not the only element that determines the net benefit per dollar spent for a given state. For example, Georgia received the highest estimated net benefit per dollar spent of $0.89, whereas its ARRA highway disbursement ranked 9th among the 48 states. This finding shows that a state's neighborhood structure also affects its net benefit per dollar spent. Thus, directing funds toward improving neighborhood structures could be considered to improve states' returns per dollar spent when future highway funds are disbursed.

A caveat should be noted. The cutoff value $\overline{q}_i$ when integrating the area shown as $\Delta CS_i^{all}$ in Figure 1 is an arbitrary value corresponding to a price ceiling of 100 times $p_{i,2010}$. Sensitivity analyses were performed to test the sensitivity of $\left(\sum_{i=1}^{48}\Delta CS_i^{all}\right)$ to changes in $\overline{q}_i$ by assuming $\overline{q}_i$'s corresponding to price ceilings of 150 and 50 times $p_{i,2010}$, which are respectively denoted as $\overline{q}_{i,+50\%}$ and $\overline{q}_{i,-50\%}$. The resulting total net benefits are $11.9 billion and $2.0 billion, respectively, yielding

average net benefits per dollar spent of \$0.44 and \$0.07, respectively. The rank order of state net benefit per dollar spent was not substantially changed by varying $\overline{q}_i$. For the cutoffs q+50 and q-50 provided the same ranks with the original cutoffs in 40 and 38 of the 48 states, and no state changed more than three ranks. The sensitivity analysis implies some confidence in determing which states received greater benefits from the 2009 ARRA highway disbursement than others, and that positive net benefits per dollar spent are likely. Nevertheless, the aforementioned sensitivity to the cutloff value suggests caution when interpreting the magnitude of the additional consumer surplus generated by the 2009 ARRA disbursement.

**Endnotes**

1. In the United States, an entitlement program is a kind of government program that offers individuals personal financial benefits to which an indefinite number of potential beneficiaries have a legal right whenever they meet eligibility conditions that are specified by the standing law that authorizes the program (Johnson 2013).

2. In fact, equation (2) embraces four different model specifications depending on whether those unobserved effects exist; i) both effects do not exist ($\mu_i = 0$, and $\lambda_t = 0$), ii) only state-specific effects exist ($\mu_i \neq 0$, and $\lambda_t \neq 0$), iii) only time-specific effects exist ($\mu_i = 0$, and $\lambda_t \neq 0$), and iv) both effects exist ($\mu_i \neq 0$, and $\lambda_t \neq 0$).

3. The log-likelihood function for equation (3)——in the following illustration our notation subsumes lagged highway disbursements into the vector of other regressors $\mathbf{X}_{i,t}$—is expressed as:

(a) $$\ln L = -\frac{NT}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[Q_{i,t} - \rho\sum_{j=1}^{N} w_{ij}Q_{j,t} - \mathbf{X}_{i,t}\boldsymbol{\beta} - \sum_{j=1}^{N} w_{ij}\mathbf{X}_{j,t}\boldsymbol{\Phi} - \mu_i\right]^2 + T\ln\left|I_N - \rho W\right|,$$

where the last term on the right hand side of the equation is the Jacobian term that addresses the endogeneity of the spatially lagged dependent variable $\sum_{i=1}^{N} w_{ij}Q_{j,t}$ (Anselin 1988). Taking the derivative of equation (a) with respect to $\mu_i$ and solving for $\mu_i$ gives:

(b) $$\mu_i = \frac{1}{T}\sum_{t=1}^{T}\left[Q_{i,t} - \rho\sum_{j=1}^{N} w_{ij}Q_{j,t} - \mathbf{X}_{i,t}\boldsymbol{\beta} - \sum_{j=1}^{N} w_{ij}\mathbf{X}_{j,t}\boldsymbol{\Phi}\right].$$

The log-likelihood function (a) is re-expressed by replacing $\mu_i$ with the right hand side of equation (b):

(c) $$\ln L = -\frac{NT}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[Q_{i,t}^* - \rho\left(\sum_{j=1}^{N} w_{ij}Q_{j,t}\right)^* - \mathbf{X}_{i,t}^*\boldsymbol{\beta} - \left(\sum_{j=1}^{N} w_{ij}\mathbf{X}_{j,t}\right)^*\boldsymbol{\Phi}\right]^2 + T\ln\left|I_N - \rho W\right|,$$

$$Q_{i,t}^* = Q_{i,t} - \frac{1}{T}\sum_{t=1}^{T} Q_{i,t}$$

$$\left(\sum_{j=1}^{N} w_{ij}Q_{j,t}\right)^* = \sum_{j=1}^{N} w_{ij}Q_{j,t} - \frac{1}{T}\sum_{t=1}^{T}\left(\sum_{j=1}^{N} w_{ij}Q_{j,t}\right),$$

$$\mathbf{X}_{i,t}^* = \mathbf{X}_{i,t} - \frac{1}{T}\sum_{t=1}^{T}\mathbf{X}_{i,t},$$

$$\left(\sum_{j=1}^{N} w_{ij}\mathbf{X}_{j,t}\right)^* = \sum_{j=1}^{N} w_{ij}\mathbf{X}_{j,t} - \frac{1}{T}\sum_{t=1}^{T}\left(\sum_{j=1}^{N} w_{ij}\mathbf{X}_{j,t}\right).$$

Estimates of $\beta$, $\Phi$, $\rho$ and $\sigma^2$ and maximize the full log-likelihood function (c) and were obtained following Elhorst's (2003) two-step procedure using the concentrated maximum likelihood function.

4. As an illustration, the marginal effects of a change in the price of highway usage in the first state ($i$ = 1) at a point in time are derived to demonstrate differences in demand curves among states. For simplicity, we transform equation (3) into N dimensional matrix form:

(d) $\boldsymbol{Q} = \rho W\boldsymbol{Q} + \alpha \boldsymbol{j}_N + \mathbf{X}\boldsymbol{\beta} + W\mathbf{X}\boldsymbol{\Phi} + \boldsymbol{\mu} + \boldsymbol{\varepsilon}$ ,

where $j_N$ is an $N \times 1$ vector of ones. Equation (d) can be re-expressed as:

(e) $\boldsymbol{Q} = \rho W\boldsymbol{Q} + \boldsymbol{P}\beta_p + W\boldsymbol{P}\phi_p + \mathbf{A}$,

where $\boldsymbol{P}$ is an $N \times 1$ price vector, $\beta_p$ and $\phi_p$ are scalar parameters, and $\mathbf{A}$ contains the other terms in equation (d) that are not involved in calculating the marginal effects. The total marginal effect of a price change on highway demand for the given state ($i$ = 1) is:

(f) $$\frac{\partial \boldsymbol{Q}}{\partial P_{i=1}} = (I - \rho W)^{-1}(\boldsymbol{i}_1\beta_p + W\boldsymbol{i}_1\phi_p),$$

where $\boldsymbol{i}_1' = [1, 0, \cdots, 0]_N$. Equation (f) can be re-expressed as:

(g) $$\frac{\partial \boldsymbol{Q}}{\partial P_{i=1}} = (I - \rho W)^{-1}\begin{bmatrix} \beta_p + w_{11}\phi_p \\ w_{21}\phi_p \\ \vdots \\ w_{n1}\phi_p \end{bmatrix}.$$

Let $v_{ij}$ be an ($i$, $j$) element of $(\mathrm{I} - \rho W)^{-1}$, then equation (g) can be solved as:

(h) $$\frac{\partial \boldsymbol{Q}}{\partial P_{i=1}} = \begin{bmatrix} v_{11}\beta_p + \phi_p \sum_{k=1}^{n} v_{1k} w_{k1} \\ v_{21}\beta_p + \phi_p \sum_{k=1}^{n} v_{2k} w_{k1} \\ \vdots \\ v_{n1}\beta_p + \phi_p \sum_{k=1}^{n} v_{nk} w_{k1} \end{bmatrix}.$$

The first element of the vector in equation (h) denotes the direct effect of $P$ on $Q$ for a given state ($i$ = 1), the other elements of the vector represent the indirect effects on $Q$ for the other states ($i \neq 1$) and the sum of all elements in (h) is the total marginal effect across the 48 states. The marginal effects of $P$ in (h) vary across states because the elements in $(\mathrm{I} - \rho W)^{-1}$ and the elements in $W$ differs in value depending on the spatial unit where an initial shock occurs.

5. The gasoline-price data in \$/gallon were converted to \$/mile using approximation of an average mileage rate of 25 miles/gallon according to the report by Litman and Doherty (2009).

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*Industry Issue Paper*

# A New Modal Classification System for Public Transportation

**by Arthur Guzzetti and John W. Neff**

*The gathering of public transportation statistics requires a system for classifying data by mode. The majority of naming conventions have consistently recognized transit operations as "heavy rail," "commuter rail," and "light rail" for the past 40 years (although some others still use older terms). New systems now emerging have unique characteristics, which have led some classifying organizations such as the National Transit Database (NTD) to begin using terms such as hybrid rail for light rail type or self-propelled passenger vehicles operated on freight rail tracks and regulated by the Federal Railroad Administration , and which were formerly classified as commuter rail or light rail until 2001, and streetcars which are electric rail circulator passenger vehicles operated primarily in streets in congested central city areas and reported as light rail until 2011. Similarly, NTD began designating some bus operations, reported as part of the general bus category until 2011, as bus rapid transit, which meets specific service criteria, as commuter bus for bus operations with significant closed door distances from distant suburbs to central cities; the remainder of bus service remained classified as simply bus. This presentation will take inventory of all types of bus and rail mode classifications, discuss the issues associated with changing classifications, and put forth a revised classification of transit modes.*

## PROBLEMS IN PUBLIC TRANSPORTATION MODAL CLASSIFICATION SCHEMES

Classification systems for collection and publication of transit operating and financial data identify modes to allow the analysis and comparison of service using different vehicles and with different operating characteristics. Changes, or a lack of change, to the names and number of basic modes of three most used transit data collection and publication modal classification systems have led to confusion and inaccurate data reporting. The three publications are the American Public Transit Association's (APTA) *Public Transportation Fact Book*, the Federal Transit Administration's (FTA) *National Transit Database* (NTD), and the Bureau of the Census *American Community Survey* (ACS). In the case of the FTA database, three modes that existed in the 2011 NTD were divided into two or three modes. The name of the single 2011 mode in each case was retained as one of the names of the new modes. Thus, the name that represented the old mode in its entirety in 2011 represented only a subset of those data in 2012. No new name was created to match the total of the new sets of two or three modes. This leads to potential confusion where the original named mode and the new part of that mode with the same name are thought to define the same set of agencies, and that there has been decline rather than growth in data associated with that mode.

Table 1 illustrates this problem. Table 1 counts only agencies that reported to the NTD in the year listed. All transit rail systems and whether or not they are included in NTD reports is reported in APTA's *Public Transportation Fact Book Appendix A: Historical Tables*. The screened back cells in Table 1 indicate that there is not a category to report summations of these pairs of modes in the NTD, and these data do not appear in the NTD.

**Table 1: Number of Agencies Reporting Rail Modes of Service to the NTD, 2010 Compared to Later Years After Additional Modes Added**

| Mode | Before Change 2010 | Reporting New Modes Optional | | Reporting New Modes Required | |
|---|---|---|---|---|---|
| | | 2011 | 2012 | 2013 | 2014 |
| Light Rail | 31 | 24 | 23 | 23 | 23 |
| Streetcar | -- | 7 | 10 | 11 | 11 |
| Unreported Total | 31 | 31 | 33 | 34 | 34 |
| Commuter Rail | 25 | 24 | 24 | 23 | 24 |
| Hybrid Rail | --- | 4 | 4 | 5 | 5 |
| Unreported Total | 25 | 28 | 28 | 28 | 29 |

Data Sources: Federal Transit Administration. *National Transit Database.* Washington, annual 1979 to 2014.

Reporting a mode of service that belongs in the new category was optional in 2011 and 2012 but was required beginning in 2013. In 2010 there were 31 light rail systems, but in 2011 there were only 24. Where did the seven light rail systems go? They became streetcar system, of course, but since there is no summation mode totaling these two modes, it is not obvious. There are tables of other data such as passengers, vehicle miles, etc., where it will not be apparent that the two years of light rail data are for different groups of systems. As will be discussed in the next section, APTA now uses another name to represent the total and alleviate this problem.

The census data classification, in contrast, has changed little in the last century and results in misreporting of travel behavior because the mode names are unrelated to current technology or the names of transit modes with which commuters are familiar. This paper will describe the history of the three modal classification systems, describe the current difficulties with each of them, and propose a limited solution to those problems.

Using a confused or outdated naming system for transit modes may lead to errors in analysis of the impact of future rail system investments and the value of existing systems. Future investment decisions may be based, in part, on the costs and results of existing systems as recorded in standardized accounting systems such as the NTD. When the classification of rail systems is changed to include finer divisions into more categories but old names are retained for some of them, the possibility exists for comparing different groups of systems in an analysis without being aware of which systems are included in the two groups before and after the change in the classification system.

The retention of antiquated names in the collection of journey-to-work data by the census may lead to errors in analysis. The use of classification names for rail modes no longer associated with them in everyday language has led to demonstrable erroneous reporting in census data. In multi-mode rail areas this can lead to errors in the analysis of modal impacts when using census data for analysis.

## APTA AND FTA RAIL CLASSIFICATION SCHEMES

The American Street Railway Association (ASRA), APTA's original predecessor, was founded in 1882. The ASRA and its successors published statistics in verbatim proceedings of their conventions, but the first stand-alone document of national data is still available; *Electric Railway Operations*, was published by the APTA predecessor American Electric Railway Association (AERA) in 1922. That publication differentiated Electric Railway (comparable to current light rail) into City Lines and Interurban Lines. In 1942, the American Transit Association began publishing the *Transit Fact Book*, which was renamed the *Public Transportation Fact Book* in 2000. Agencies operating service comparable to heavy rail were not included until 1933 and commuter rail until 1977. The years that modes were introduced or their names changed for APTA, FTA, and census classifications are shown in Table 2 for modes comparable to light rail, in Table 3 for modes comparable to heavy rail, and Table 4 for modes comparable to commuter rail. By 1977, the APTA classification reached what was considered the modern differentiation of basic modes, which lasted until 2011: light rail, heavy rail, and commuter rail. Tables 2 and 4 report inclusive category names and partial category names. Inclusive category names are summary mode names that include all data for all light rail type or commuter rail type modes. Partial category names define only a portion of the systems included in the inclusive category name.

The Federal Transit Administration's National Transit Database was first published in 1979 and included light rail and heavy rail type modes under the older names, streetcar and rapid rail. APTA had adopted the modern terms light rail and heavy rail in 1974. The NTD would not adopt those names as options until 1984 and as standard names until 1993. The term light rail was coined in 1972 (Thompson 2003). Adoption of heavy rail to describe what had been called subway and elevated differentiated the two primary urban rail modes by their capacity: light rail carried smaller volumes of traffic and heavy rail carried larger volumes of traffic. The terms streetcar and subway and elevated for the two primary urban rail modes differentiated physical attributes of the system. But both modes operated in tunnels and elevated structures so the names did not actually describe what the differences between the two modes were. Commuter rail was added in 1984.

Beginning in 2011, the NTD differentiated light rail into light rail and streetcar and differentiated commuter rail into commuter rail and hybrid rail. The problem created by this action is that light rail in 2010 and 2011 were a different set of agencies, and commuter rail in 2010 and 2011 were a different set of agencies. A new classification name to summarize the two new modes in each set was not introduced. Therefore, there is no continuation of total all light rail and total all commuter rail between 2010 and 2011. The decrease of "light rail" between the two classifications could be interpreted as a decrease in overall light rail; similarly, the decrease in "commuter rail" between the two classifications could be interpreted as a decrease in overall commuter rail. The fact that the new classification hybrid rail in 2012 included two former light rail agencies and two former commuter rail only further complicates matters. Because of this, the NTD no longer reports continuous summary data among rail modes from before and after 2011.

**Table 2: Light Rail Type Mode Names, Data Years of Use in Publications**

| Time Period | American Public Transit Association | | National Transit Database | | Census | |
|---|---|---|---|---|---|---|
| | Inclusive Category | Partial Categories | Inclusive Category | Partial Categories | Inclusive Category | Partial Categories |
| 1890 | | | | | Street Railway | Electric Railway, Cable Railway, Horse Railway, Steam Railway |
| 1902-1911 | | | | | --- | Street and Electric Railway, Interurban Railway |
| 1912-1921 | | | | | Surface Railway | --- |
| 1922-1924 | Electric Railway | Urban Electric Railway, Interurban Electric Railway | | | Surface Railway | --- |
| 1925-1930 | Electric Railway | City Lines, Interurban Lines | | | Surface Railway | --- |
| 1931 | Electric Railway | City Lines, Interurban Lines, Commutation Lines, Suburban Lines | | | Surface Railway | --- |
| 1932-1935 | Electric Railway | City Lines, Interurban Lines | | | Surface Railway | --- |
| 1936 | City Surface Lines | --- | | | Street Railway | --- |
| 1937 | Railway | City Railway, Interurban | | | Street Railway | --- |
| 1938-1941 | Railway | City Railway, Interurban | | | | |
| 1942-1959 | Surface Railway | --- | | | | |
| 1960-1973 | Surface Railway | --- | | | Streetcar or Trolley Car | --- |
| 1974-1978 | Light Rail | --- | | | Streetcar or Trolley Car | --- |

**Table 2: continued**

| Time Period | American Public Transit Association | | National Transit Database | | Census | |
|---|---|---|---|---|---|---|
| | Inclusive Category | Partial Categories | Inclusive Category | Partial Categories | Inclusive Category | Partial Categories |
| 1979-1983 | Light Rail | --- | Streetcar | --- | Streetcar or Trolley Car | --- |
| 1984-1992 | Light Rail | --- | Streetcar or Light Rail | --- | Streetcar or Trolley Car | --- |
| 1993-2010 | Light Rail | --- | Light Rail | --- | Streetcar or Trolley Car | --- |
| 2011-2014 | Surface Rail | Light Rail, Streetcar | --- | Light Rail, Streetcar | Streetcar or Trolley Car | --- |

No Summary data published or modes not reported in summary data publications.
– No partial categories reported for inclusive category or no inclusive category summing partial categories.

Sources:

American Electric Railway Association. *Electric Railway Operations.* Washington, annual 1922 to 1931.
American Public Transit Association. *Transit Fact Book.* Washington, annual 1975 to 1999.
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Federal Transit Administration. *National Transit Database.* Washington, annual 1979 to 2014.
U.S. Census Bureau. *American Community Survey.* Washington, annual 2010 to 2014.
U.S. Census Bureau. *United States Census.* Washington, 1960 to 2010.

## Table 3: Heavy Rail Type Mode Names, Data Years of Use in Publications

| Time Period | American Public Transit Association | National Transit Database | Census |
|---|---|---|---|
| | Inclusive Category | Inclusive Category | Inclusive Category |
| 1907-1911 | | | Included In "Street and Electric Railway" |
| 1912-1926 | | | Elevated and Subway Railway |
| 1927-1933 | Included In "Electric Railway" | | Elevated and Subway Railway |
| 1933-1935 | Rapid Transit | | Elevated and Subway Railway |
| 1936 | Rapid Transit Lines | | Elevated and Subway Railway |
| 1937 | Included In "Railway" | | Included In "Street Railway" |
| 1938-1941 | Included In "Railway" | | |
| 1942 | Rapid Transit | | |
| 1943-1959 | Subway and Elevated | | |
| 1960-1973 | Subway and Elevated | | Subway or Elevated |
| 1974-1978 | Heavy Rail | | Subway or Elevated |
| 1979-1982 | Heavy Rail | Rail Rapid | Subway or Elevated |
| 1983-1989 | Heavy Rail | Rapid Rail | Subway or Elevated |
| 1990-1992 | Heavy Rail | Rapid Rail or Heavy Rail | Subway or Elevated |
| 1993-2014 | Heavy Rail | Heavy Rail | Subway or Elevated |

No Summary data published or modes not reported in summary data publications.

Sources:

American Electric Railway Association. *Electric Railway Operations.* Washington, annual 1922 to 1931.
American Public Transit Association. *Transit Fact Book.* Washington, annual 1975 to 1999.
American Public Transportation Association. *Public Transportation Fact Book.* Washington, annual 2000 to 2015.
American Public Transportation Association. *Public Transportation Fact Book Appendix A: Historical Tables.* Washington: American Public Transportation Association, annual 2013 to 2016.
American Transit Association. *Electric Railway Operations.* Washington, annual 1932 to 1933.
American Transit Association. *Transit Operations.* Washington, annual 1935 to 1941.
American Transit Association. *Transit Industry of the United States.* Washington, 1942.
American Transit Association. *Transit Fact Book.* Washington, annual 1944 to 1974.
Bureau of the Census. *Central Electric Light and Power Stations and Street and Electric Railways 1912.* Washington, 1915.
Bureau of the Census. *Census of Electrical Industries: 1917, Electric Railways*. Washington, 1920.
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Federal Transit Administration. *National Transit Database.* Washington, annual 1979 to 2014.
U.S. Census Bureau. *American Community Survey.* Washington, annual 2010 to 2014.
U.S. Census Bureau. *United States Census.* Washington, 1960 to 2010.

**Table 4: Commuter Rail Type Mode Names, Data Years of Use in Publications**

| Latest Data Year | American Public Transit Association | | National Transit Database | | Census | |
|---|---|---|---|---|---|---|
| | Inclusive Category | Partial Categories | Inclusive Category | Partial Categories | Inclusive Category | Partial Categories |
| 1960-1976 | | | | | Railroad | --- |
| 1977-1983 | Commuter Rail | --- | | | Railroad | --- |
| 1984-2010 | Commuter Rail | --- | Commuter Rail | --- | Railroad | --- |
| 2011 | Passenger Railroad | Commuter Rail, Hybrid Rail | --- | Commuter Rail, Hybrid Rail | Railroad | --- |
| 2012-2014 | Regional Railroad | Commuter Rail, Hybrid Rail | --- | Commuter Rail, Hybrid Rail | Railroad | --- |

No Summary data published or modes not reported in summary data publications.
– No partial categories reported for inclusive category or no inclusive category summing partial categories.

Sources:
American Public Transit Association. *Transit Fact Book.* Washington, annual 1975 to 1999.
American Public Transportation Association. *Public Transportation Fact Book.* Washington, annual 2000 to 2015.
American Public Transportation Association. *Public Transportation Fact Book Appendix A: Historical Tables.* Washington: American Public Transportation Association, annual 2013 to 2016.
Federal Transit Administration. *National Transit Database.* Washington, annual 1979 to 2014.
U.S. Census Bureau. *American Community Survey.* Washington, annual 2010 to 2014.
U.S. Census Bureau. *United States Census.* Washington, 1960 to 2010.

APTA has dealt with this problem by creating two new classification categories to maintain continuity between 2010 and later data sets. In 2011 through 2014, APTA has used "surface rail" as a term for the sum of the new light rail and streetcar modes and a continuous historical comparison to the former light rail. In 2011, APTA used "passenger railroad" as a term for the sum of the new commuter rail and hybrid rail and in 2012 through 2014, APTA used "regional railroad" as a sum for commuter rail and hybrid rail. Passenger railroad was used for only one year because it might have been incorrectly viewed as including intercity passenger railroad. This allowed APTA to publish continuous data for the old light rail and a sum of the new light rail and streetcar modes and the old commuter rail and the new commuter rail and hybrid rail modes.

The difficulty of selecting a new modal classification scheme to summarize light rail and streetcar and commuter rail and hybrid rail is the difference in the basis of modal names. Some names have been based on the generalized location of the light rail type modes, e.g., streets, urban, surfaces, interurban, but commuter rail is based on a description of activity. The APTA selection as a summary mode for the new light rail and the new streetcar cannot, of course, use either of those names and uses a name popular over a century ago, surface rail. This name is chosen because most light rail and streetcar service is provided on the surface rather than in tunnels or elevated structures, and all other historical names appear to be inappropriate. This was the primary location of each mode, and was the basis of the classification by the census as far back as 1917, as reported in this quote.

> "Classification according to character of roadway. This classification presents statistics of elevated and subway roads in comparison with the surface roads, or those which are essentially surface. The elevated and subway group includes those having elevated or subway trackage in excess of surface trackage."
>
> (Bureau of the Census, *Census of Electrical Industries 1917: Electric Railways*. Washington, 1920.)

"Surface rail" and "regional rail" are currently used as inclusive summary mode names in the *APTA Public Transportation Fact Book, Appendix A: Historical Tables* because that publication compares transit data over time on sum tables for nearly a century. Historical comparison requires categories that may have changed names over time but do not change the group of systems and type of operation included over time. Regional rail is taken from European usage and describes shorter travel within a region on systems operating on current or former freight railroad type infrastructure. In the *APTA Public Transportation Fact Book*, which was data solely for the reported year, summary categories are not needed for continuity and have not been used.

## CENSUS RAIL CLASSIFICATION SCHEMES

The current rail classification scheme used in the census *American Community Survey* to describe the primary mode of travel by commuters is outdated and results in obviously incorrect data. These data are nevertheless published by the census and may result in erroneous planning, research, and political decision making.

The original census classification scheme used from 1890 through 1937 was for statistical reports describing the transit railway industry in the same manner as the current APTA *Public Transportation Fact Book* and the FTA *National Transit Database*. Most of those publications differentiated between surface railway and elevated and subway railway. The last census publication of rail transit data was for 1937 data.

Beginning in 1960, the census began collecting, as part of the *Decennial Census* and then the *American Community Survey*, data on mode of transportation for commuters. For transit they adopted variations on the categories used to collect transit data earlier in the century. Rail modes were "streetcar or trolleycar," "subway or elevated," and "railroad." In 1960, these names were not inconsistent with industry practice and represented the rail service available at that time. The common names used to describe these modes by transit passengers and the industry have changed since then, but the census names have not. A passenger who rides a light rail system likely does not know the correct commute mode response on a census form is "streetcar or trolley car."

Census data indicate the commuter frequently selects the wrong rail mode. The effect of this is shown on Table 5, which reports commute mode data from the 2014 *American Community Survey*. Each of these urbanized areas has a single type of transit rail service. In many cases the reported number of commuters is skewed to modes of service not operated in that urbanized area.

**Table 5: Number of Rail Commuters Reporting Alternative Rail Modes of Travel in Single Mode Urbanized Areas, 2014 American Community Survey**

| Urbanized Area/ Transit Agency | Only Available Mode of Service in 2014 | Number of Commuters Using Streetcar and Trolley Car | Number of Commuters Using Subway and Elevated | Number of Commuters Using Railroad | Percent Correct Response |
|---|---|---|---|---|---|
| St, Louis, MO-IL: Bi-State Development Agency | Light Rail | 587 | 5,914 | 981 | 7.85% |
| Denver-Aurora, CO: Regional Transportation District | Light Rail | 1,348 | 9,460 | 3,717 | 9.28% |
| Atlanta, GA: Metropolitan Atlanta Rapid Transit Authority | Heavy Rail | 330 | 21,633 | 2,336 | 89.03% |
| Houston, TX: Metropolitan Transit Authority of Harris County | Light Rail | 931 | 701 | 703 | 39.87% |
| Nashville-Davidson, TN: Nashville Metropolitan Transit Authority | Commuter Rail | 9 | 182 | 206 | 51.89% |
| Sacramento, CA: Sacramento Regional Transit District | Light Rail | 2,299 | 2,012 | 2,195 | 35.34% |

Modes not operated in urbanized area.

Source: U.S. Census Bureau. *American Community Survey.* Washington, 2014.

St. Louis' only rail service is a light rail system. In the census, light rail would be classified as streetcar and trolley car. But only 7.85% of commuters in St. Louis reporting any form of rail transit as their primary commute mode report the mode correctly. The light rail line does go into a tunnel in downtown St. Louis and crosses bridges and other elevated structures, thus, subway and elevated could be a logical choice, and is incorrectly selected by 79% of respondents. Changing this classification would require action by the census.

## APTA AND FTA BUS CLASSIFICATION SCHEMES

Similar to the way they divided light rail and commuter rail into two modes in 2011, the NTD also divided the existing bus category into three modes: bus rapid transit, commuter bus, and bus. As with the rail modes, one new category has the same name as the previous total category. This does not present the same degree of problem as the division of light rail and commuter rail does. The new bus modes are operational divisions using the same technology and often the same vehicles. APTA, in the *Public Transportation Fact Book, Appendix A: Historical Tables*, addresses this problem by simply having a "total bus" column that adds the three new modes together and provides continuity with historical data.

Table 6 illustrates this problem for bus modes. In this, case the number of agencies in the basic mode continues to increase. In the rail categories, light rail and streetcar are an either/or mode selection as are commuter rail and hybrid rail. In bus, however, a bus mode agency before 2011 may have operated what is now termed bus service as well as bus rapid transit service and commuter bus service. An agency reporting the new modes will likely also continue to report the bus mode. The increase in bus systems between 2011 and 2012 results in part from the 2010 Census delimiting 32 more urbanized areas than the 2000 Census, and the expansion of existing urbanized areas brought some formerly rural systems into urbanized areas. If an agency has both directly operated and purchased transportation service for any of these modes, the agency would have been counted twice.

**Table 6: Number of Agencies Reporting Bus Modes of Service to the NTD, 2010 Compared to Later Years After Additional Modes Added**

| Mode | Before Change 2010 | Reporting New Modes Optional | | Reporting New Modes Required | |
|---|---|---|---|---|---|
| | | 2011 | 2012 | 2013 | 2014 |
| Bus | 584 | 609 | 688 | 695 | 700 |
| Bus Rapid Transit | --- | 5 | 4 | 7 | 10 |
| Commuter Bus | --- | 36 | 72 | 110 | 120 |
| Unreported Total | 584 | 650 | 764 | 802 | 830 |

No Summary data published.

Source: Federal Transit Administration. *National Transit Database.* Washington, annual 1979 to 2014.

## CONCLUSION

In 2011, the National Transit Database subdivided its light rail modal category into three modes, commuter rail into two modes, and bus into three modes. In each case, the former names, light rail, commuter rail, and bus, were used to identify one of the new subsets of the old modes. This use of the same name for different modes, which include different sets of transit agencies, may lead to errors in historical analysis. APTA, in its historical statistics, uses new names to include all of the previous modes in order to report data that is inclusive of the entire former modal sets of transit systems. The current modes that were included in light rail in the NTD before 2011 are summarized under the name surface rail in APTA historical reports. The current modes that were included in commuter rail in the NTD before 2011 are summarized under the name regional railroad in APTA historical reports. The current modes that were included in bus in the NTD before 2011 are summarized under the name total bus modes in APTA historical reports. This allows a continuity of reporting data for the same groups of transit agencies for historical comparisons. These new names are subject to change if more appropriate names are proposed; but they would be changed back to 2011 names to maintain the new continuity.

The Bureau of Census continues to use names for rail modes that date back as far as 1912. These names are no longer in everyday use and are selected incorrectly for journey-to-wok modes by respondents to the American Community Survey. This may lead to incorrect analysis using census data. These names would need to be changed by the census.

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Bureau of the Census. *Census of Electrical Industries, 1932, Electric Railways and Motor-Bus Operations of Affiliates and Successors*. Washington, 1934.

Bureau of the Census. *Census of Electrical Industries, Electric Railways 1922*. Washington, 1925.

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U.S. Census Bureau. *American Community Survey.* Washington, annual 2010 to 2014.

U.S. Census Bureau. *United States Census.* Washington, 1960 to 2010.

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# 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

| | |
|---|---|
| 2015 | David Ripplinger |
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| 2013 | Jack Ventura |
| 2012 | Ken Button |
| 2011 | Alan R. Bender |
| 2010 | B. Starr McMullen |
| 2009 | Richard Gritta |
| 2008 | Kenneth Button |
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| 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) |

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| | |
|---|---|
| 2016 | Robin Lindsey |
| 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**

| | |
|---|---|
| 2016 | Wayne Talley |
| 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. |

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Wayne K. Talley (1998-2000)
K. Eric Wolfe (1993-1998)
Kevin H. Horn (1993-1998)
Anthony M. Pagano (1987-1993)
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**Recipients of the TRF Best Paper Award**

2016 Ian Savage and Caroline Miller, *Does the Income Level of a Neighborhood Affect the Price Elasticity of Demand for Transit?*

2016 Tony Diana, *Does Market Concentration Foster Scheduled Arrival Reliability? A Case Study of Ten U.S. Airports*

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?*

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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*.

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1994 Brian Shaffer and James Freeman, *Variation in Producer Responses to Automobile Fuel Economy Mandates*.

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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.

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   *Journal Article:*

   Kane, Louis R. "Grain Transport Rate Projections." *Transportation Journal* 2 (1999): 20-40.

   *Journal Article with Multiple Authors:*

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*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.

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