JOURNAL of the TRANSPORTATION RESEARCH FORUM

Volume 51, Number 2 Summer 2012

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

Journal of the Transportation Research Forum

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

Disclaimer:

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

Subscriptions:

The Journal of the Transportation Research Forum (JTRF) is distributed to members of the Transportation Research Forum and subscribers.

Currently, the JTRF is published three times per year. Annual subscriptions are available to the general public for $150 and must be purchased for a calendar year.

An electronic version (PDF format) is available for $50 per Journal or single Journal articles for $10 each.

Subscriptions and/or membership applications may be obtained from the following office or online at www.trforum.org

ISSN 1046-1469

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

or apply online at www.trforum.org

Journal of the Transportation Research Forum
Volume 51, Number 2 • Summer 2012

Table of Contents

On the cover: Transportation economists, engineers, and planners historically have focused on the various modes of transportation and the associated infrastructure. Few researchers have paid attention to the start or end of the trips – the parking garage. This research gap is filled by Mazhar Ali Awan's review of Shannon Sanders McDonald's book, "The Parking Garage: Design and Evolution of a Modern Urban Form."

BOOK REVIEW

A Message from the JTRF Co-General Editors

The Summer 2012 issue of *JTRF* contains the usual wide variety of contemporary transportation topics that is the distinguishing characteristic of *JTRF*. Topics in this issue include the following:

- Methods for estimating household trip rates
- Feasibility of an intermodal terminal in rural Texas
- Border zone mass transit demand
- High occupancy toll lane performance
- Microsimulation of automobile markets
- Rail rate index for grain
- The feasibility of shared-use vehicles to reduce emissions

In "Comparison of Alternative Methods for Estimating Household Trip Rates of Cross-Classification Cells with Inadequate Data," Judith Mwakalonge and David Badoe investigate the forecast performance of a traditional trip rate forecast model with alternative models that address the shortcomings of the traditional model. The objectives of their analysis are to develop trip generation models using cross-classification Analysis (CCA) and Multiple Classification Analysis (MCA) and compare how the models perform predicting San Francisco travel in the base year. A second objective is to compare the performance of both CCA and MCA models in short-term and long-term forecast applications. The third objective is to present alternative models for addressing the shortcomings of CCA and to compare the forecast performance of the alternative methods compared to CCA and MCA models. The authors found that the traditional CCA model provides more consistent travel predictions than any of the alternative methods.

Stephen Fuller et al. examines the feasibility of an intermodal terminal in west Texas and its impact on reducing roadway maintenance costs and CO_2 emissions in "Feasibility of an Intermodal Terminal in Rural Texas to Enhance Marketing and Transportation Efficiency." The authors had three objectives: first, to determine the economic feasibility of an intermodal terminal in west Texas; second, to estimate reduced road maintenance expenditure from investment in the terminal; and third, to estimate the reduction in CO_2 emissions associated with the terminal, and the value of the reduced emissions. These objectives were accomplished with a spatial model of the U.S. cotton industry that features details of cotton, handling, storage, and transportation activities. The authors found that the terminal is economically viable. They also found that it would annually reduce truck travel and lower road maintenance costs by approximately $1 million and reduce CO_2 emissions from 42% to 47%.

In "High Occupancy Toll Lane Performance Under Alternative Pricing Policies," Thomas Light explores how alternative pricing and operating policies influence revenue generation, level of service, and travel time costs for High Occupancy Toll (HOT) lane facilities. The paper seeks to understand how some of the design features influence the performance of HOT lane facilities with emphasis on the implications of setting tolls to achieve different goals. To do this, Light presents a simple, flexible HOT lane model, and the model is examined numerically. The author finds that the way in which tolls are set can influence competing measures of HOT lane performance. He also notes that other operating characteristics such as number of lanes designated as free and priced and whether carpools are allowed to ride free or must pay a toll to access the HOT lanes can significantly affect HOT lane performance.

Thomas Fullerton and Adam Walke examine whether economic conditions in Mexico influence public transportation ridership levels in "Border Zone Mass Transit Demand in Brownsville and Laredo." The authors point out that there is a long-standing assumption that pedestrian border crossers form a substantial portion of transit ridership in border cities. The author's purpose is to determine whether, and to what extent, this claim can be quantified. They specify a model of the demand for public transportation that is a function of transit fares, the level of service, urban population, income, car ownership, the price of substitutes such as auto travel, northbound pedestrian traffic, and the real exchange rate index. The authors found that the volume of pedestrian border crossings in both Brownsville and Laredo, Texas, is positively related to changes in transit ridership. They also found that the real exchange rate index in Laredo is negatively related to transit ridership, implying that peso appreciation increases transit utilization in Laredo.

In "Microsimulating Automobile Markets: Evolution of Vehicle Holdings and Vehicle Pricing Dynamics," Brent Selby and Kara Kockelman develop a market model for the evolution of new and used personal vehicle fleets. They point out that vehicle ownership decisions are important for estimates of emissions, gas tax revenue, energy security, and pavement management. One of the principal objectives is the simulation of vehicle purchase and resale decisions via an auction process among individual households in the market for new and used vehicles. They say their work focuses on the choices made when households are offered the option to buy new or used personal vehicles, when the market clearing is achieved by auction-driven price changes. The authors apply the model to Austin, Texas, using survey data over a 20-year period that highlights the model's flexibility and reasonable response to multiple inputs.

Adam Sparger and Marvin Prater develop improved grain rail rate indices for unit trains and shuttle trains in a "Comprehensive Rail Rate Index for Grain." The authors state that their new indices are an improvement upon past grain rail rate indices by including information from the secondary rail car market, fuel surcharges, and tariff rates into a weekly index for the 1997-2011 period. The authors have two objectives: first, develop comprehensive rail rate indices for grain in unit trains and shuttle trains utilizing all three major components of the total price paid by shippers; second, compare the rail rate indices for grain with a rail cost index to measure how documented changes in the rail market beginning around 2004 have impacted grain rates. The authors found that their indices show grain rail rates generally higher than other indices. They found that for unit trains the increase in grain rates between 2004 and 2009 was related to the increase in railroad input costs. Only since the beginning of 2009 has there been a consistent difference between rail grain rates and railroad input costs. The authors noted that in contrast to unit train rates, the increase in shuttle train rates during the recession appears to be consistent with changes in railroad input costs.

In "Evaluating the Efficacy of Shared-Use Vehicles for Reducing Greenhouse Gas Emissions: A U.S. Case Study of Grocery Delivery," Erica Wygonik and Anne Goodchild compare the CO_2 emissions from the use of personal vehicles to shared-use vehicles for grocery shopping in Seattle, Washington. The authors point out that shared-use services reduce employee trips to work, household trips to the transfer station, and household trips to schools by collecting passengers and goods into one vehicle. The paper extends the existing literature in this area by modeling the logistical details of routing and scheduling, and by comparing the results of an American case study to European case studies. The authors found that U.S. and European case studies had consistent results, that low customer density results in greater opportunities for emissions decreases and that logistical efficiencies can account for about 50% of CO_2 reductions.

Michael W. Babcock
Co-General Editor

Kofi Obeng
Co-General Editor

Comparison of Alternative Methods for Estimating Household Trip Rates of Cross-Classification Cells With Inadequate Data

by Judith L. Mwakalonge and Daniel A. Badoe

This paper investigates the forecast performance of a traditional cross-classification model and alternative models that seek to address the shortcomings of traditional cross-classification analysis, specifically when it has cells with inadequate data. The study uses five cross-sectional datasets collected in the San Francisco Bay Area in 1965, 1981, 1990, 1996, and 2000. Alternative models, estimated with travel data collected in the base year, were assessed for their ability to replicate the number of trips made by households in each cell of a cross-classification matrix and at the traffic zone level, respectively, in each of the five years. The results showed that the traditional cross-classification analysis (CCA) model, notwithstanding having a few unreliable cells provided more consistent predictions of travel than any of the alternative methods. They also show that it is better to synthesize trip rates for only those cells of the cross-classification matrix with inadequate data rather than to adjust the entire trip-rate matrix as is currently the practice.

INTRODUCTION

The four-step Urban Transportation Modeling System (UTMS) continues to be the method adopted by the majority of metropolitan planning organizations for simulating traffic volumes using the links of urban transportation networks (TRB 2007). This paper focuses on trip generation, the first step of the four-step UTMS. Given the sequential nature of UTMS, improved forecast accuracy at the trip generation stage is important to reducing errors in the forecasts emanating from the final step of the process.

A number of methods for accomplishing trip generation are documented in the travel demand modeling literature. These include multiple linear regression (Cotrus et al. 2003, Ewing et al. 1996), cross-classification analysis (Walker and Peng 1991, Rengaraju and Satyakumar 1995), discrete choice models (Zhao 2000), fuzzy logic models, and artificial neural networks (Huisken 2000). However, of these methods, cross-classification analysis (CCA) is the most widely used in practice (Rengaraju and Satyakumar 1994).

Cross-classification analysis involves the use of trip rates (i.e., trips per person or trips per household) to compute regional travel demand. Recognizing the heterogeneity in regional populations, the approach first divides the population into relatively homogeneous groups or categories based on two or three household attributes. Thereafter, a trip rate is calculated for each relatively homogeneous group. The technique is non-parametric in that it does not assume any probabilistic distributional relationship between the dependent and explanatory variables. Furthermore, the method makes use of the raw data obtained from a household travel behavior survey directly, and its simplicity has made it attractive to practitioners (Rengaraju and Satyakumar 1994). The method, however, has its shortcomings.

First, given the typical size of travel survey samples that most planning agencies have available for travel demand model development, cross classifying the sample into a large number of relatively homogeneous categories leaves some cells with few or no observations for the computation of trip rates. These problematic cells typically exist at the extreme ends of the cross-classification matrix. As an example, the proportion of households in an urban area with a single person and owning three

or more vehicles is likely to be very small. A simply drawn random sample of households from the regional population may include few or no households with such characteristics. Therefore, cross classifying the travel data could result in such a cell being empty, making it impossible to estimate directly a trip rate for it.

Second, the estimated trip rates of the cross-classification matrix suffer from differential reliability resulting from the differences in the numbers of households in each cell for trip-rate computation. Trip rate is the expected number of trips a household makes per day. This difference in reliability could result in counterintuitive trip-rate progressions in the trip-rate matrix. These two shortcomings among others documented in the literature have spurred researchers to investigate new techniques for improving upon the basic model. Examples of these studies include those by Rengaraju and Satyakumar (1994), Kikuchi and Rhee (2003), and Stopher and McDonald (1983). The most known of these methods, proposed by Stopher and McDonald (1983), makes use of multiple classification analysis (MCA). However, its implementation also raises concerns. First, it modifies all the trip rates obtained using the CCA procedure, notwithstanding several cells in the matrix having adequate data for computation of reliable trip rates. Second, sometimes implementation of the MCA procedure results in the computed trip rate for some of the cells of the classification matrix having a negative sign, which is not meaningful. The analyst addresses the resultant negative trip-rates problem by assigning a zero trip rate to such a cell (Ortuzar and Willumsen 2001). Assigning zeros to cells that either had values earlier or were empty in CCA is unrealistic.

Kikuchi and Rhee (2003) applied a fuzzy optimization method to synthesize missing cell values and adjust cell values with abnormal behavior when compared to neighboring cells. However, the fuzzy optimization method, like the MCA, changes the cell values of the entire classification matrix instead of the cells with inadequate data. Additionally, the fuzzy optimization technique requires knowledge of a programming language and is therefore not readily accessible to transportation planners, which limits its use by practitioners.

Thus, while these attempts to remedy the weaknesses of CCA are recognized, the problem of adjusting the trip rates that are derived from the observed sample persists. Additionally, it appears that no study has investigated both the short-term and long-term forecast performance of the methods proposed to remedy the shortcomings of CCA. Guevara and Thomas (2007) recommended not using the MCA method proposed by Stopher and McDonald (1983). However, their recommendation was based in part on analysis done using a single origin-destination survey data. Further, they conducted their model evaluation using forecasted land use scenarios and not observed land use and travel characteristics. The above discussion motivates an investigation into alternative methods or modifying existing methods for synthesizing trip rates for cross-classification cells with no data that do not require the modification of trip-rate values for cells with adequate data.

Specific objectives of the paper are, first, to develop trip generation models using CCA and MCA, respectively, and to compare how the models perform in the prediction of travel in the base year. The second objective is to compare the performance of both CCA and MCA models in short-term and long-term forecast applications. The third is to present alternative methods for addressing the shortcomings of CCA and to compare the forecast performance of these alternative methods against the models developed using CCA and MCA, respectively.

The rest of the paper is organized as follows. In the second section, the theory underlying the existing and proposed methods for estimating a trip rate for a cross-classification cell with no data are presented. The third section presents the descriptive analysis of the travel data used in the research. The fourth section presents the model estimation results and results from applying the alternative methods in predicting travel. Finally, the last section presents a summary and conclusions drawn from the study.

ALTERNATIVE MODELS FOR SYNTHESIZING TRIP RATES FOR CROSS-CLASSIFICATION CELLS WITH NO DATA

This section presents a brief description of the theory underlying the alternative models investigated in this study. The existing models considered in this study include CCA and MCA models. The current practice is to employ the MCA technique that modifies the whole cross-classification trip-rate matrix. However, MCA can also be used to estimate trip rates for empty cells and unreliable cells. Therefore, this study makes use of MCA models and techniques employed in estimating missing values to compute trip rates for empty and less reliable cells. The techniques for estimating missing values investigated in this research are Multiple Imputation (MI) and K-Nearest Neighbor (KNN). The theory of each of these methods is discussed in turn below.

Cross-Classification Analysis

As discussed in the introduction, CCA involves the computation of trip rates typically at the household level. However, recognizing the heterogeneity in travel behavior that exists among households in an urban region, households are grouped according to two or more characteristics that are strongly associated with trip-making behavior. Households belonging to each defined group are therefore assumed relatively similar in trip-making behavior. The model's basic assumption is that household trip rates remain stable over time for defined household stratifications. It should be noted that the model could be developed for each trip purpose. However, in this research, we consider trips made across all trip purposes by a household and two-household attributes for defining groups of similar travel behavior. The household trip rate for each defined group is calculated as:

(1)
$$\bar{y}_{mn} = \frac{\sum_{h=1}^{H_{mn}} y_{mn}^{h}}{H_{mn}}$$

Where

m, n = values of two-household attributes used in defining homogeneous groups (cells)

$\bar{y}_{mn}$ = trip rate for cell of cross-classification matrix with household attribute values *mn*

y_{mn}^{h} = trips made by household *h* in cell *mn*

H_{mn} = total number of households in cell *mn*

Multiple Classification Analysis

MCA is similar to multiple regression analysis with dummy variables. The approach is applicable where the dependent variable is quantitative and the explanatory variables are categorical, represented by dummy variables. Therefore, MCA with one categorical variable is equivalent to one-way Analysis of Variance (ANOVA), similarly MCA with two categorical variables correspond to two-way ANOVA (Retherford and Choe 1993). Stopher and McDonald (1983), as a remedy to the shortcomings of CCA, were the first to apply the technique in trip generation analysis. Thereafter, several researchers (Ortuzar and Willumsen 2001, Wardman and Preston 2001, Abdel-Aal 2004) applied the method. However, none of the mentioned studies used MCA to estimate trip rates for empty and/or unreliable cells only. Rather, they employed it to modify the whole trip-rate matrix. The general mathematical form of the MCA model is expressed as:

(2) $$\bar{y}_{mn} = G_{\mu} + \alpha_m + \beta_n + \varepsilon_{mn}$$

Where

$\bar{y}_{mn}$ = the trip rate for a cell in a cross-classification matrix with household attribute values *mn*
G_{μ} = the grand mean of trips made by the households in the dataset
α_m = the column-effect for column *m* of a cross-classification matrix
β_n = the row-effect for row *n* of a cross-classification matrix
ε_{mn} = error term

For comparison purposes, this study reviews and investigates three MCA models designated as MCA1, MCA2, and MCA3. The first, MCA1, takes the following form (Guevara and Thomas 2007).

(3) $\bar{y}_{mn} = \mathrm{G}_{\mu} + \alpha_{\mathrm{m}} + \beta_{\mathrm{n}} \quad \{ \begin{matrix} \forall m \in M \\ \forall n \in N \end{matrix}$

Where

(4) $G_{\mu} = \dfrac{\sum_{h=1}^{H} y^h}{H}$

(5) $\alpha_m = \dfrac{\sum_{n \in N} y^h_{mn}}{\sum_{n \in N} H_{mn}} - G_{\mu}$

(6) $\beta_n = \dfrac{\sum_{m \in M} y^h_{mn}}{\sum_{m \in M} H_{mn}} - G_{\mu}$

N, M = the respective number of classes for the two stratification variables
n, m = the values of two household attributes used in defining homogeneous groups (cells)
H = the total number of households
y^h = the trips made by household *h*
G_{μ} = the grand mean of trips made by the households in the dataset
α_m = column effect for column *m* of a cross-classification matrix
β_n = row effect for row *n* of a cross-classification matrix
ε_{mn} = error term

The second MCA model, MCA2, takes the same mathematical form as the first one except the row and column effects are calculated as weighted means, which therefore takes into consideration the unequal number of observations in the cells of the cross-classification matrix (Stopher and McDonald 1983, Guevara and Thomas 2007).

(7) $\alpha_m = \left(\sum_{n \in N} w_{mn} \bar{y}_{mn} / \sum_{n \in N} w_{mn} \right) - G_{\mu}$

(8) $\beta_n = \left(\sum_{m \in M} w_{mn} \bar{y}_{mn} / \sum_{m \in M} w_{mn} \right) - G_{\mu}$

Where

w_{mn} = weighting factor for cell *mn*

$\bar{y}_{mn}$ = trip rate for a cell in a cross-classification matrix with household attribute values *mn*

G_{μ} = overall mean that is average number of trips per household

β_n = row effect for row *n* of a cross-classification matrix

α_m = column effect for column *m* of a cross-classification matrix

The third, MCA3, is from an MCA regression of household trips on all classification variables. However, the model is slightly different from ordinary least squares in that when calculating the marginal effect of an explanatory variable, the other explanatory variables are held constant at their mean values in the entire sample (Retherford and Choe 1993). The model's mathematical form is

$$(9)\quad \bar{y}_{mn} = a + \sum_{n \in N} \beta_n X_n + \sum_{m \in M} \alpha_m X_m$$

Then the trip rates for the categories of variable X_n are calculated as:

$$(10)\quad \bar{y}_{mn} = a + \sum_{n \in N} \beta_n X_n + \sum_{m \in M} \alpha_m \bar{X}_m$$

Where

X_n, X_m = 1 if the *n*th or m^{th} element of X is observed, and equals a zero otherwise.

$\bar{y}_{mn}$ = trip rate for a cell in a cross-classification matrix with household attribute values *mn*

β_n = row effect for row *n* of a cross-classification matrix

α_m = column effect for column *m* of a cross-classification matrix

n and *m* are initial classes that are considered as reference classes, hence a constant *a* to be estimated is added.

Multiple Imputations (MI)

MI is a three-step approach that employs regression analysis to impute missing values (Rubin 1976). The first step is to estimate a model using observations with complete data and, thereafter, use the estimated model to fill in the missing values. The second step is to estimate a model using a complete data set with both observed and imputed values. For this case, the analyst substitutes predicted values for the missing values to create imputed datasets. The procedure is repeated until the analyst has the desired number of imputed datasets. Usually, three to ten imputed datasets are desirable (Wayman 2003). Finally, the estimates from steps one and two are combined to account for the uncertainty regarding the imputation. In mathematical form, the joint distribution is a function of the marginal and conditional distribution and it is represented as (Horton and Kleinman 2007):

$$(11)\quad f(Y_h, X_h) = f\left(Y_h^{miss}, Y_h^{obs} \mid X_h, \boldsymbol{\beta}\right) P\left(X_h\right)$$

Where

Y^{obs} = observed dependent variable (trip rates)

Y^{miss} = missing dependent variable

X_h = vector of explanatory variables (two household attributes used in defining homogeneous groups (cells))

β = vector of parameters

$f\left(Y_h^{miss}, Y_h^{obs} \mid X_h, \boldsymbol{\beta}\right)$ = Conditional probability distribution

$P(X_h)$ = Marginal probability distribution

The final imputed estimate is the combined estimate that follows Rubin's procedure (Rubin 1976), which is a simple average of individual estimates from the observed and imputed datasets. Mathematically this is,

$$(12) \quad \bar{y}^h = (1/K)\sum_{i=1}^{K} \hat{y}_i$$

$$(13) \quad \bar{y}_{mn} = \sum_{h=1}^{H_{mn}} \bar{y}_{mn}^h / H_{mn}$$

Where
K= number of imputed full datasets
All other variables are as defined earlier.

K-Nearest Neighbor (KNN)

KNN is a technique for estimating unobserved data based on the characteristics and values of the observed nearest data. KNN technique has been widely applied in medical research and geosciences (Muhammad et al. 2004) but less so in transportation. The simplicity of the KNN method motivated its application in estimating empty cells in the trip-rate matrix. Selection of nearest cells is determined based on similarity in characteristics between the filled nearest cells and the empty cell. For example, a missing trip rate for a single-person household with four or more vehicles may have similar characteristics to a single-person household with three vehicles, since both households have surplus vehicle supply. Therefore, a missing cell value is computed by weighting the predetermined nearest cell values as follows,

$$(14) \quad \bar{y}_{mn} = \sum_{\substack{n\in N \\ m\in M}} w_{mn}\, \hat{y}_{mn} / \sum_{\substack{n\in N \\ m\in M}} w_{mn}$$

$$(15) \quad w_{mn} = o_{mn} / \sigma_{mn}^2$$

Where
σ_{mn}^2 = variance estimate for the mn^{th} nearest cell
o_{mn} = number of observations in the mn^{th} nearest cell

All other variables are as defined earlier.

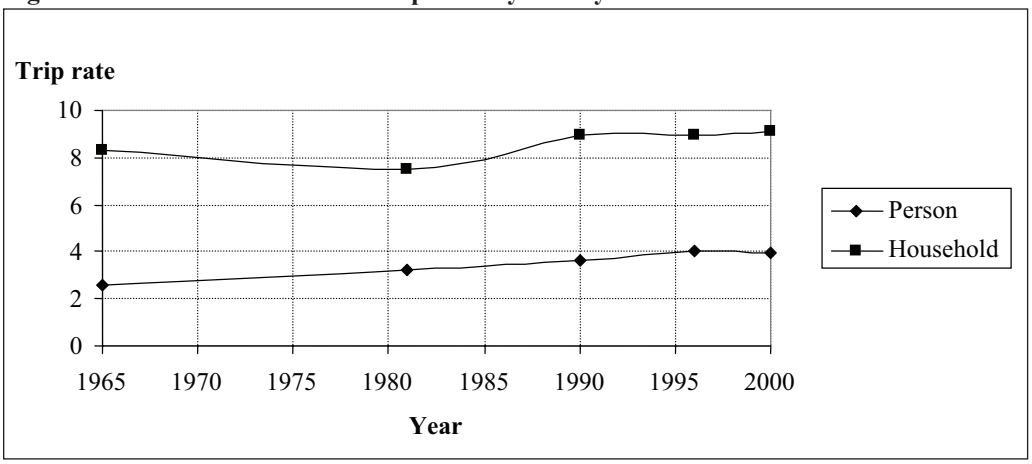
DATA

The research uses five cross-sectional datasets collected in different years (1965, 1981, 1990, 1996, and 2000) in the San Francisco Bay area. The 1965 dataset has information on more than 20,000 households, while the 1981 dataset has information on more than 7,000 households. The 1990 dataset has information on more than 9,000 households, while the 1996 dataset is the smallest sample with information on a little more than 3,600 households. Finally, the 2000 dataset has information on more than 15,000 households. The analysis presented below uses the sample data and unlinked trips. Information on linked trips and the trip-linking procedure are in MTC (2003). The five datasets are comparable since the region has remained relatively stable in terms of geographic area. However, the survey instrument changed from home interview to telephone interview (1981 onward), and trip recall to activity diary (1996 and 2000 are activity-based surveys). In the context of how the alternative modeling methods are to be assessed in this study, the differences in instruments are unlikely to pose any problems.

Trip Rate Distribution

With the exception of 1981, Figure 1 shows that the household trip rate in the Bay Area remained relatively stable. There is a noticeable decrease in household trip rates in 1965 compared with 1981. Purvis (1994) reported that other major cities, namely Dallas and Denver, exhibited the same pattern in trip-making behavior and noted this decrease in trip rate. However, at the individual level, there is a progressive increase in trip rate from 1965 to 1996, and thereafter it remained stable.

Figure 1: Household and Person Trip Rate by Survey Year



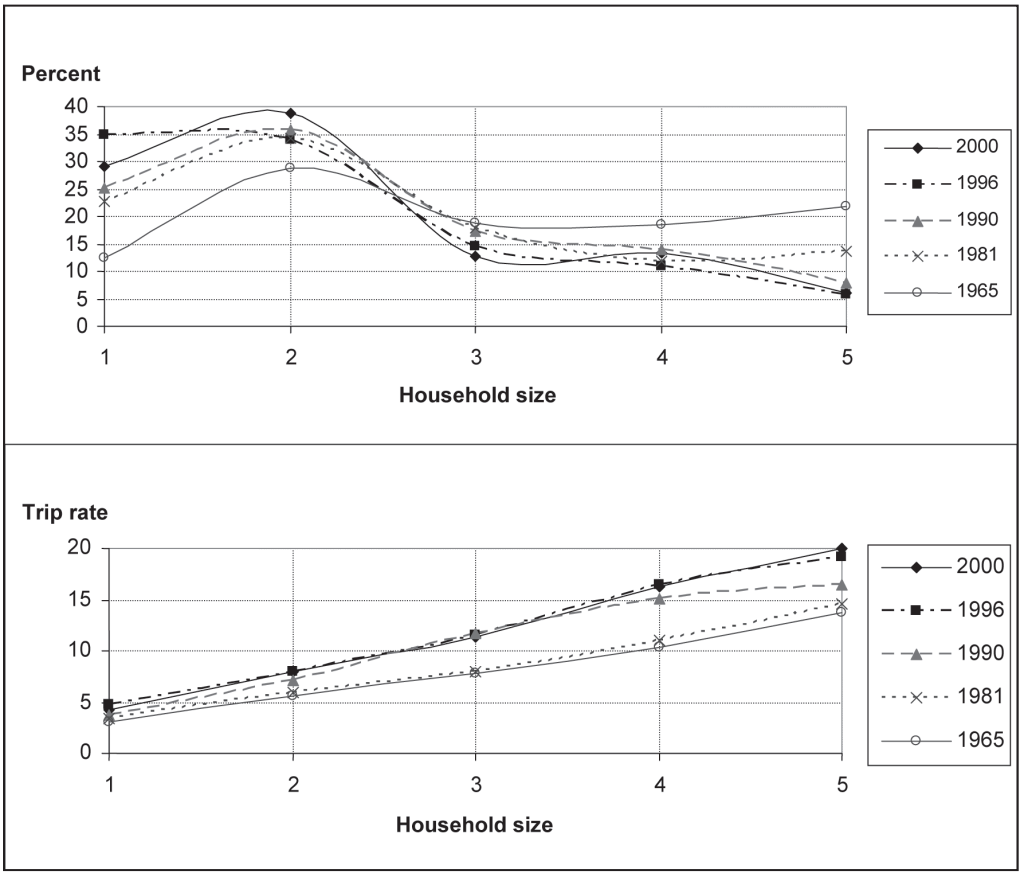
Household Size

Household size affects travel demand; on average, the larger a household, the greater its activity needs and the number of trips made. Figure 2(a) shows household size distribution across the analysis years. Generally, there is an increase in single person households and a decrease in four or more person households from 1965 to 2000. Although the trip rate increases with household size, it increases at different rates over the analysis years across different household groups. For example, there is a dramatic increase in travel demand from 1981 to 1990 for households with three to four persons. This increase is partly explained by a more than 10% increase in the working age group (age 36 to 55), a small trip-rate increase of 0.43 trips for single-person households and an increase of 1.30 trips for two-person households. All else being equal, travel behavior was stable from 1965 to 1981 and from 1996 to 2000 as shown in Figure 2 (b).

Vehicle Ownership

People purchase vehicles with the aim of increasing their mobility and activity participation. On average, the greater the number of vehicles owned by a household, the greater the number of trips they are likely to make by vehicle. As observed, the percentage of households with no vehicle was higher in 1981 than in 1965. With the exception of the 1990 household trip rates, there is a consistent, although minor increase in trip rate for zero-vehicle households from 1965 to 2000, and a stable trip rate for households with one or more vehicles. Households with three or more vehicles had a much higher trip rate in 1990 than in any of the other years. Figure 3 is a graphical summary of these details.

Figure 2: (a) Household Size Distribution by Survey Year
(b) Trip Rate by Household Size for Each Survey Year



Variable Selection

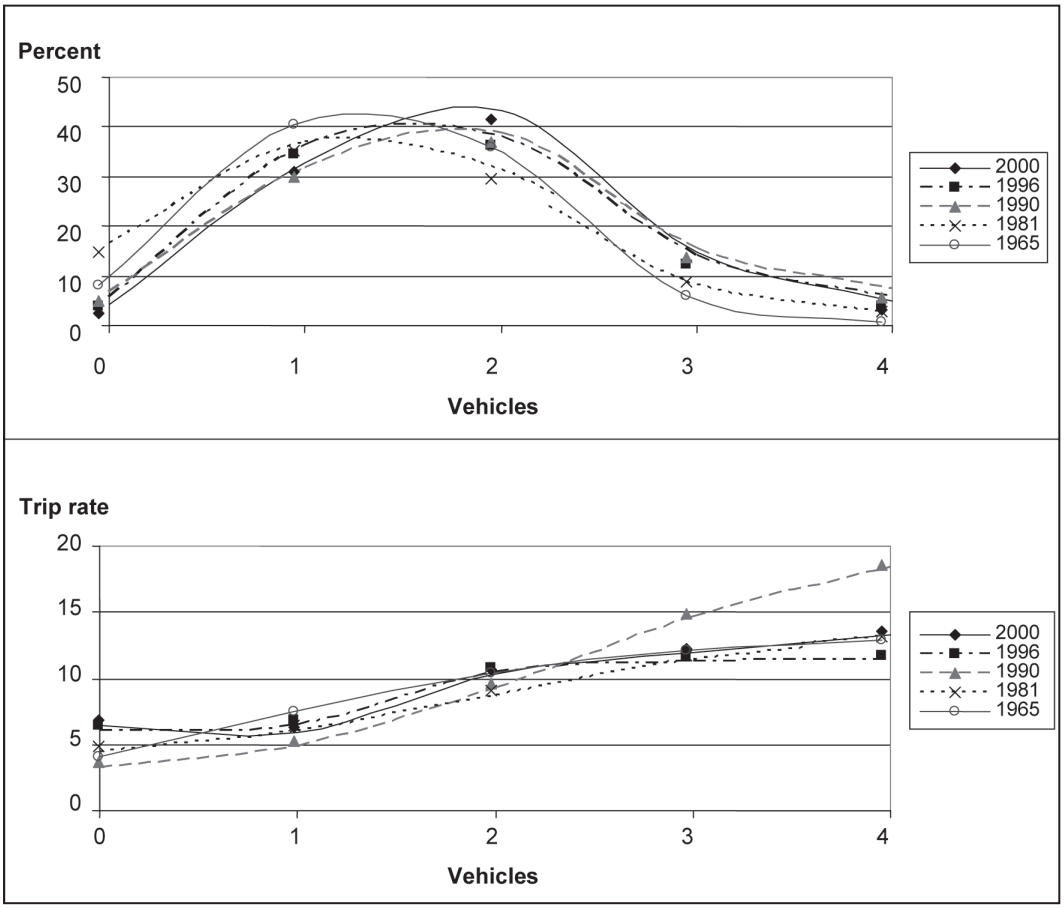
The 1965 dataset has eight potential explanatory variables. The objective was to select two or three that could capture most of the variation in household trips. In accomplishing this objective, the study uses analysis of variance procedure (ANOVA), and the results are in Appendix A. At the 5% level of significance, the results show that house tenure (own or rent) and dwelling type, with respective probabilities of 0.2942 and 0.2556, were not statistically significant. Variables that were statistically significant are household size, number of household members with drivers licenses and household income, the number of motorcycles owned by a household and vehicles owned by a household. Appendix A shows that the number of households with drivers licenses correlates moderately with the number of vehicles owned by a household. Consequently, the analysis uses the number of vehicles owned by a household and household size as the stratification variables.

EMPIRICAL TEST

Test Procedure

The assessment of the performance of the alternative methods for developing a cross-classification model for trip generation involved five steps. In the first step, the study estimates the CCA model and the three MCA models with the 1965 data using the household as the modeling unit. The

Figure 3: (a) Vehicle Ownership Distribution by Survey Year
(b) Trip Rate by Vehicle Ownership for Each Survey Year



second step uses each of the four models to predict travel collectively made by households in each classification cell and by households in each traffic analysis zone in 1965, respectively. The latter assessment of model performance at the traffic zone level is important because trip distribution, a step in the four-step UTMS, requires as input trip productions and trip attractions at the traffic zone level. In the third step, the study uses the four models in step one to predict household travel in each cross-classification cell in 1981, 1990, 1996, and 2000, respectively. In the fourth step, each of the methods proposed for synthesizing trip rates for cross-classification cells with little or no data was applied to predict the trip rate for only those cells of the traditional cross-classification matrix considered unreliable. The household trip rates from the traditional CCA were preserved for the cells with enough observations. Finally, the fifth step uses the cross-classification matrices from the fourth step to predict household travel in all the years for which data were available.

RESULTS AND DISCUSSION

Estimated Models

The results of the model estimation in the first step are in Table 1. They show that each cell has a different number of observations. For example, for single-person households, the sample size for

those with no vehicle is 1,062, whereas for those with four or more vehicles it is 11. Given that the reliability of the trip rate for each cell is a function of the number of observations in the cell, it is apparent that there are differences in cell reliability in the CCA model due to each cell having a different number of observations.

In the descriptive analysis presented earlier, there was a monotonically increasing relationship between trip rate and household size (Figure 2b). A similar relationship was observed between trip rate and vehicle ownership (Figure 3b). However, this increasing trend is not consistently observed when one examines how trip rates that are conditional on a specific household size vary with vehicle ownership or how trip rates that are conditional on a specific vehicle ownership level vary with household size in the CCA matrix. As an example, Figure 2b shows that for a household size of one (single-person household), trip-rate increases with increasing vehicle ownership until a household vehicle ownership level of three when it drops, and then increases thereafter for those single person households that have four or more vehicles. A similar observation in Figure 3b regards the relationship between trip rate and household vehicle ownership for two-person households.

As expected, Table 1 shows a counterintuitive progression in trip rates in the less reliable cells (e.g., single-person household with three vehicles). To address this problem, the practice is to employ MCA; and the results of doing so for the different methods are in Table 1. MCA2 yielded a trip rate for single-person households with no vehicle that has a negative sign. Since a negative trip rate is unrealistic, the practice is to set it to zero (Ortuzar and Willumsen 2001). However, for illustration, Table 1 preserves this negative-valued trip rate although in the forecasting analysis done later it is set to zero. MCA1 and MCA3 yielded household trip rates with trends that are consistent with expectation; that is, higher household trip rates for higher values of vehicle ownership and household size, respectively.

Prediction of Travel at the Household and Traffic Zone Level In 1965

Travel demand models need to provide accurate predictions to guide decisionmakers in infrastructure investment decisions. Therefore, the four models were applied in turn to predict travel in the base year at the disaggregate household level, and their performance was judged based on the coefficient of determination (R^2) and the percent mean absolute error (PMAE) calculated as,

$$PMAE = \left(\sum_{\substack{m \in M \\ n \in N}} \left(\frac{y_{mn}^{pred} - y_{mn}^{obs}}{y_{mn}^{obs}} \right) * 100 \right) / (N * M) \tag{16}$$

Where

y_{mn}^{pred} = predicted number of trips made by households in cell *mn*

y_{mn}^{obs} = observed number of trips made by households in cell *mn*

N, M = the respective number of classes for the two stratification variables

Table 2 shows an assessment of the accuracy of each of the four models in predicting the trips made by each household in 1965. Of the three MCA models, MCA1 has the smallest PMAE while MCA2 has the largest error value. Contributing to the high PMAE value of MCA2 was its complete failure to predict any trips made by single person households with no vehicles. (Column three of row four in Table 1 has a negative trip rate that is set to zero in forecasting). Also shown in columns two and three are the results of regressing the observed number of daily trips made by the households in each cross-classification cell against the number of daily trips to be made by the households in each cross-classification cell predicted by each model (CCA, MCA1, MCA2, or MCA3). They indicate that for CCA, MCA1, and MCA3, the estimated slope coefficients are almost one while the slope coefficient of MCA2 is about 0.92. Based on the coefficients of determination, MCA1, MCA2, and MCA3 explain the variation in household trips in the 1965 data very well; MCA1 and MCA3

Table 1: Estimated CCA and MCA Models Using 1965 Data

Household Size	Model	Number of Vehicles 0	1	2	3	4+	Total
1	CCA	2.201	3.644	4.756	3.941	5.000	3.084
	MCA1	1.091	3.108	4.567	5.290	5.486	3.908
	MCA2	-1.675	1.827	4.757	6.586	7.314	3.084
	MCA3	2.028	3.710	5.182	6.404	6.571	4.376
	No. of obs. in cell	1062	1367	82	17	11	2539
2	CCA	3.658	5.417	6.216	7.161	6.889	5.603
	MCA1	3.051	5.068	6.527	7.250	7.445	5.868
	MCA2	0.844	4.346	7.276	9.105	9.833	5.603
	MCA3	3.446	5.128	6.601	7.823	7.989	5.794
	No. of obs. in cell	556	3016	2081	193	54	5900
3	CCA	5.406	7.240	8.159	8.940	8.978	7.773
	MCA1	4.927	6.944	8.403	9.126	9.322	7.744
	MCA2	3.014	6.516	9.446	11.275	12.003	7.773
	MCA3	5.181	6.863	8.335	9.558	9.724	7.529
	No. of obs. in cell	175	1543	1575	448	89	3830
4	CCA	6.774	9.111	10.999	11.797	12.046	10.362
	MCA1	7.328	9.345	10.804	11.527	11.723	10.145
	MCA2	5.603	9.105	12.034	13.864	14.592	10.362
	MCA3	7.613	9.295	10.768	11.99	12.156	9.961
	No. of obs. in cell	106	1283	1818	424	130	3761
5+	CCA	9.173	11.883	14.46	16.367	16.270	13.769
	MCA1	10.813	12.830	14.289	15.012	15.208	13.630
	MCA2	9.010	12.512	15.441	17.271	17.999	13.769
	MCA3	10.981	12.663	14.135	15.358	15.524	13.329
	No. of obs. in cell	139	1444	2137	523	211	4454
Total	CCA	3.587	7.089	10.018	11.848	12.576	8.346
	MCA1	5.442	7.459	8.918	9.641	9.837	8.259
	MCA2	3.587	7.089	10.018	11.848	12.576	8.346
	MCA3	5.998	7.680	9.153	10.375	10.541	8.346
	No. of obs. in cell	2038	8653	7693	1605	495	20484

Note: CCA-Cross Classification Analysis; MCA1-Multiple Classification Analysis Model 1; MCA2-Multiple Classification Analysis Model 2; MCA3-Multiple Classification Analysis Model 3.

explain more than 99% of the variation in household trips in the 1965 dataset, while MCA2 explains about 97.64% of the variation.

In the conventional four-step UTMS modeling approach, regardless of the unit employed in trip generation, the predicted trips by households are aggregated to traffic zone levels for input into the trip distribution or modal choice step. Consistent with this procedure, the study combines the trips predicted for households by each of the four models to traffic zone levels. Afterwards, the observed zonal trips were regressed against the predicted zonal trip productions yielded by each of the four models. A summary of the results are in the bottom half of Table 2. Based on the coefficient of

determination (R^2) CCA, MCA1, and MCA3 explain over 96% of the variance in the observed trips at the traffic zone level while MCA2 explains slightly over 95% of this variance. Using the mean absolute error measure (PMAE), the CCA model yields the lowest error measure of 12.373. The MCA models, which were supposed to address the shortcomings of CCA, yield zonal predictions of trips that have greater error compared with the CCA model. The results from regressing the observed zonal trips against the predicted zonal trips using the four models are presented in columns two and three of the bottom half of Table 2.

Table 2: Performance of 1965 CCA and MCA Models in Predicting Trips at Household and Traffic Zone Levels in 1965

Household Level				
Model	**Intercept**	**Slope**	**R2**	**PMAE**
CCA	0.00	1.0000	1.0000	0.000
MCA1	140.68	0.9939	0.9957	9.264
Standard Error	140.00	0.0136		
t-value	1.00	73.0700		
MCA2	466.63	0.9222	0.9764	26.887
Standard Error	323	0.0299		
t-value	1.44	30.8400		
MCA3	-61.52	1.0090	0.9972	9.605
Standard Error	114.00	0.0111		
t-value	-0.54	90.6100		
Traffic Zone Level				
Model	**Intercept**	**Slope**	**R2**	**PMAE**
CCA	-15.97	1.0266	0.9661	12.373
Standard Error	8.39	0.0115		
t-value	-1.90	89.5900		
MCA1	-10.07	1.0318	0.9633	12.895
Standard Error	8.68	0.0120		
t-value	-1.16	86.0600		
MCA2	8.04	0.9968	0.9556	14.730
Standard Error	9.38	0.0128		
t-value	0.86	77.9100		
MCA3	-16.80	1.0280	0.9654	12.758
Standard Error	8.48	0.0116		
t-value	-1.98	88.7100		

Note: CCA-Cross-Classification Analysis; MCA1-Multiple Classification Analysis Model 1; MCA2-Multiple Classification Analysis Model 2; MCA3-Multiple Classification Analysis Model 3.

Forecast Performance of Alternative Models

The models estimated in the first step were then used to forecast travel in the years for which data were available. The time lag between 1965 and 1981, 1990, 1996, and 2000 provided for an assessment of the medium- to long-term forecast performance of these models. The results of the analyses are in Table 3. The regression results of the observed number of daily trips made by households in each cross-classification cell against the corresponding number of daily trips predicted by the models (CCA, MCA1, MCA2, or MCA3) for each cross-classification cell are in columns three to nine of this table. Examining the 1981 results, with the exception of MCA2 all the models explained in excess of 98% of the variation in the observed trips made by households. Values of the percent mean absolute error measure in column 10 of Table 3 for all the models were smallest for 1981 compared with those in any of the other years. Focusing on 1981, CCA had the smallest percent mean absolute error measure value of 11.69% as shown in the tenth column of the second row of Table 3.

For 1990, the models explain slightly more than 91% of the variation in household trips, which is about 7% less than the explained variation using the 1981 dataset for CCA, MCA1, and MCA3 models. Additionally, the error measures for CCA, MCA1, and MCA3 in 1990 is approximately double their corresponding values in 1981, while that for the MCA2 model declines. The CCA model performs better than the MCA models for the 1990 application. The three models, CCA, MCA1, and MCA3, explain trip variation at the household level in excess of 96% using the household trip data in 1996. MCA2, on the other hand, explains 85% of the variation in the trip data, which is about 11% less than that for the other three models. In terms of the error measure, the CCA model ranks first – it has the lowest percent average error, followed by MCA1 and then MCA3. The MCA2 model yields the highest percent average error and therefore ranks fourth.

The application of the models to generate long-term forecasts for 2000 yielded results similar to those obtained for 1990 and 1996. In terms of explaining trip variation at the household level, all the models performed well by explaining more than 96% of the total variation in the trips made by households. In general, the CCA model yields travel forecasts with lower error values compared with error values obtained with forecasts by the MCA models in all the applications.

Prediction of Household Trip Rates for Cross-Classification Cell with Inadequate Data

As discussed earlier, a challenge in the use of CCA is the possibility of having a number of cells of the cross-classification matrix having few or no observations. The primary concern under such circumstances should be with the problematic cells only; that is, those with little or no data and not the entire trip-rate matrix. However, current planning practice calls for modifying the entire household trip-rate matrix obtained by CCA (Ortuzar and Willumsen 2001) rather than just the problematic cells. This study applies the same MCA models to estimate a household trip rate for each of the problematic cells only, while preserving the household trip rates obtained from ordinary CCA for the remaining cells. In addition to the MCA models, two other techniques for estimating missing cell values, namely KNN and MI, are employed for predicting household trip rates for only those empty and/or unreliable cells, and after the forecast performance of all these models are assessed. It is noted that no study was found in the literature that employed MI or KNN to synthesize household trip rates for cross-classification cells with inadequate data.

From the ordinary cross-classification analysis results using the 1965 data presented in Table 1, each cell of the cross-classification matrix had observations. However, based on the threshold number of observations required for statistical reliability reported in Ortuzar and Willumsen (2001) the number of observations for three of the cells was low. The defining characteristics of these cells are: (1) single-person households owning three vehicles, (2) single-person households owning four or more vehicles, and (3) two-person households owning four or more vehicles. Therefore, the three

Table 3: Performance of 1965 Models in Predicting Trips by Households in Each Cross-Classification Cell in Years 1981, 1990, 1996, and 2000

Year	Model	Intercept			Slope				
		Coefficient	Standard Error	t-value	Coefficient	Standard Error	t-value	R^2	PMAE
1981	CCA	39.89	37	1.09	1.0188	0.0138	73.84	0.9960	11.69
	MCA1	112.47	78	1.43	1.0156	0.0304	33.37	0.9800	15.98
	MCA2	365.71	181	2.02	0.8775	0.0668	13.14	0.8820	33.18
	MCA3	21.98	52	0.42	1.0247	0.0200	51.3	0.9910	16.00
1990	CCA	18.15	265	0.07	1.2393	0.0719	17.24	0.9280	27.12
	MCA1	240.30	287	0.83	1.2377	0.0811	15.26	0.9100	30.14
	MCA2	287.76	268	1.07	1.0909	0.0670	16.27	0.9200	32.40
	MCA3	42.40	249	0.17	1.2059	0.0659	18.31	0.9360	31.17
1996	CCA	32.93	53	0.62	1.3164	0.0385	34.23	0.9807	27.62
	MCA1	58.80	68	0.86	1.3191	0.0503	26.21	0.9676	29.87
	MCA2	145.59	145	1.00	1.1724	0.1015	11.55	0.8529	34.54
	MCA3	46.13	70	0.66	1.2681	0.0490	25.88	0.9668	28.96
2000	CCA	173.75	221	0.79	1.2776	0.0337	37.95	0.9840	28.76
	MCA1	354.12	247	1.43	1.2588	0.0377	33.39	0.9800	31.47
	MCA2	467.17	334	1.40	1.1201	0.0460	24.36	0.9630	31.91
	MCA3	285.78	281	1.02	1.2229	1.2229	29.41	0.9740	31.45

Note: CCA-Cross Classification Analysis; MCA1-Multiple Classification Analysis Model 1; MCA2-Multiple Classification Analysis Model 2; MCA3-Multiple Classification Analysis Model 3.

MCA models, and KNN and MI in turn, were used to synthesize household trip rates for just these three cells that would otherwise have unreliable household trip rates. The remaining cells of the matrix retained their household trip rates obtained from the ordinary cross-classification analysis (CCA). The estimated household trip rates for these cells obtained by the CCA, MCA, KNN, and MI are in Table 4. For each of the three cells, the estimated household trip rate by MCA1, MCA2, MCA3, KNN, or MI exceeds the corresponding household trip rate obtained by CCA. Further, replacing the household trip rates obtained by CCA for the three problematic cells with those yielded by any of the models results in the expected increasing relationship between household trip rates and increasing household size or increasing vehicle ownership respectively.

Forecast Performance of Household Trip-Rate Matrices Developed

Table 5 presents the values of the measures for evaluating the accuracy of household trip predictions given by the five alternative models, respectively. The measures are evaluated using the observed trips and the predicted trips made by households in each cross-classification cell.

Evaluation of the accuracy of predictions of travel in 1965. In the base year (1965), MCA1 had the lowest PMAE value and therefore the best performance in predicting travel based on this measure. It is followed by MI. MCA2 had the worst performance in predicting travel, reflected by it having the highest PMAE value. The coefficient of determination is one for all the models, indicating that each explained all the variation in household trips in the base year.

Table 4: Predicted Household Trip Rates for Cells of 1965 Trip-Rate Matrix with Inadequate Data Given by Alternative Models

Model	H^1=1, V^2=3	H^1=1, V^2=4+	H^1=2, V^2=4+
Cross Classification Analysis	3.941	5.000	6.889
Multiple Classification Analysis Model 1	5.290	5.486	7.445
Multiple Classification Analysis Model 2	6.586	7.314	9.833
Multiple Classification Analysis Model 3	6.404	6.571	7.989
Multiple Imputation	5.351	6.585	8.912
K-Nearest Neighbor	6.186	7.139	8.344

1. H = Size of the household
2. V = Number of vehicles available to the household

Evaluation of the accuracy of predictions of travel in 1981. Based on the coefficient of determination, all the models explain in excess of 99% of the variation in household trips in 1981. CCA yielded the lowest PMAE value of 11.689, indicating it had a travel forecast accuracy superior to that of the other models. MCA1 had the next lowest PMAE value followed by MI, then KNN, and then MCA3. MCA2 had the highest PMAE value due to the rather large household trip rate estimates it gives for the three cells with inadequate data (see Table 4). For each model, the PMAE value in 1981 is higher than the corresponding value in 1965.

Evaluation of the accuracy of predictions of travel in 1990. The coefficient of determination using the predictions of household travel by each of the models ranges from 0.924 to 0.928, indicating that the models are able to explain in excess of 92.4% of the variation in household trips. The values of PMAE range from 27.117 for CCA to 29.392 for KNN. MCA1 has the second lowest PMAE value (27.260). This indicates that based on this measure (PMAE) the CCA model of household trip rates, notwithstanding three of the cells having inadequate data, gives more accurate household travel forecasts than those given by the other models. Immediately following this is MCA1. Again, for each model, the PMAE value in 1990 is higher than the corresponding value in 1981.

Evaluation of the accuracy of predictions of travel in 1996. The coefficient of determination evaluated using the predictions of household travel by the six models ranges from 0.975 for MCA2 to 0.981 for CCA. This indicates that the models explain in excess of 97.5% of the variation in household trips. PMAE is highest for MCA2 (31.972), indicating the worst forecast performance of household travel based on this measure. CCA has the lowest PMAE value of 27.619, indicating the best forecast performance of travel based on this measure. Immediately following it is MCA1, which has a PMAE value of 28.215. MI, with a PMAE value of 29.453, has the third best forecast performance of travel. Again, for each model, the PMAE value in 1996 is higher than the corresponding value in 1990.

Evaluation of the accuracy of predictions of travel in 2000. The coefficient of determination based on the predictions of household travel by each of the models is 0.983. This indicates that all the models are able to explain 98.3% of the variation in household trips. KNN has the highest PMAE value of 32.686, indicating the worst forecast performance of household travel based on this measure, while CCA with a PMAE value of 28.756 has the best forecast performance of household travel. MCA1, with a PMAE value of 30.147, has the next best forecast performance of household travel.

Table 5: Performance of 1965 Alternative Models in Predicting Trips by Households in Each Cross-Classification Cell in Years 1965, 1981, 1990, 1996, and 2000

		Intercept			Slope				
Year	Model	Coefficient	Standard Error	t-value	Coefficient	Standard Error	t-value	R^2	PMAE
	MCA1	-4.46	2	-2.14	1.000	0.0002	4868	1.000	2.287
	MCA2	-15.90	9	-1.83	1.001	0.0008	1193	1.000	6.245
	MCA3	-8.28	4	-2.19	1.001	0.0004	2742	1.000	4.395
	KNN	-9.78	5	-2.13	1.001	0.0004	2253	1.000	4.834
1965	MI	-9.64	5	-1.79	1.001	0.0005	1919	1.000	3.624
	CCA	39.89	37	1.09	1.0188	0.0138	74	0.996	11.689
	MCA1	35.97	36	0.98	1.020	0.0139	73	0.996	13.521
	MCA2	25.57	38	0.67	1.023	0.0145	71	0.995	16.554
	MCA3	32.38	37	0.87	1.021	72.690	0	0.996	15.279
	KNN	31.35	37	0.84	1.021	72.470	0	0.996	15.194
1981	MI	31.28	37	0.84	1.021	0.0141	72	0.995	14.208
	CCA	18.15	265	0.07	1.2393	0.0719	17	0.928	27.117
	MCA1	1.09	265	0.00	1.242	0.0720	17	0.925	27.260
	MCA2	-39.36	268	-0.15	1.250	0.0727	17	0.924	29.421
	MCA3	-15.43	266	-0.06	1.245	0.0723	17	0.925	29.126
	KNN	-19.74	267	-0.00	1.246	0.0723	17	0.925	29.392
1990	MI	-16.78	266	-0.06	1.245	0.0722	17	0.925	27.787
	CCA	32.93	53	0.62	1.3164	0.0385	34	0.981	27.619
	MCA1	23.17	54	0.42	1.320	0.0395	33	0.979	28.215
	MCA2	4.37	59	0.07	1.325	0.0432	31	0.975	31.972
	MCA3	14.02	56	0.25	1.323	0.0408	32	0.978	30.165
	KNN	12.39	56	0.22	1.323	0.0410	32	0.977	30.679
1996	MI	15.77	56	0.28	1.322	0.0408	32	0.978	29.453
	CCA	173.75	221	0.79	1.2776	0.0337	38	0.984	28.756
	MCA1	156.89	222	0.71	1.279	0.0340	37	0.983	30.147
	MCA2	127.22	227	0.56	1.281	0.0350	36	0.983	30.852
	MCA3	140.90	223	0.63	1.280	0.0342	37	0.983	32.142
	KNN	136.78	224	0.61	1.281	0.0343	37	0.983	32.686
2000	MI	138.87	224	0.62	1.280	0.0343	37	0.983	31.326

Note: CCA-Cross-Classification Analysis; MCA1-Multiple Classification Analysis Model 1; MCA2-Multiple Classification Analysis Model 2; MCA3-Multiple Classification Analysis Model 3.

SUMMARY AND CONCLUSIONS

This paper investigated the forecast performance of trip generation models based on cross-classification (CCA) and multiple classification analysis (MCA). In addition, it examined the replacement of household trip rates in unreliable cross-classification cells with values estimated by three MCA models and two methods for estimating missing values namely Multiple Imputation (MI) and K-Nearest Neighborhood (KNN). The results of the study lead to the following conclusions.

First, the methods that call for modifying the entire household trip rate matrix obtained from ordinary cross-classification analysis give a performance in prediction of household travel that is worse than that given by the methods that call for synthesizing household trip rates for cells with inadequate data only while preserving the other household trip rates obtained from ordinary cross-classification analysis. This result is evident by comparing the upper part of Table 2 to the upper part of Table 5. Thus, it is concluded that adjusting all the trip rates of a CCA matrix using MCA, the current industry standard, results in a forecasting model that is inferior to CCA and hence should be avoided by practitioners. Whenever cells with inadequate data exist in a CCA matrix, the substitution of the trip rates of these unreliable cells only with trip rates obtained from the MCA models, the MI method, or KNN results in more accurate forecasts compared with adjusting the trip rates for all the cells.

Second, even though three of the cells of the ordinary cross-classification matrix had inadequate data, the model surprisingly and consistently gave the best performance in the prediction of household travel in both the medium and the long term (see column 10 of Table 3). Thus, the basic CCA model is robust and practitioners can use it to provide credible forecasts of travel if few of the cells of the CCA matrix are unreliable. It may also indicate that the recommended minimum number of observations for a cell can perhaps be reduced and still lead to the development of reliable cross-classification models. It is for future research to determine the appropriate minimum number of observations for a cell.

Third, replacing the unreliable household trip rates of an ordinary CCA matrix with household trip rates estimated using the MCA models, KNN and MI did improve upon the performance of the cross-classification model compared with adjusting all the trip rates of the CCA matrix. Among these methods for synthesizing a household trip rate, on average, MCA1 and MI have the lowest error values (column 10 of Table 5). However, since MCA1 is subject to biases (Guevara and Thomas 2007), the MI model may be preferred over MCA1 even though MCA1 may be a simpler model compared with the MI model.

Finally, the forecast performance of cross-sectional models declines with time. For example, the corresponding PMAE values associated with each model increased with the time interval between the base and application years (see column 10 of Table 5). This certainly is logical because of the greater changes expected to occur in land use patterns, socio-demographic characteristics and attitudes of the population, transportation system characteristics, and technology with time elapsed from the base year. Thus, irrespective of the method used to synthesize household trip rates for unreliable cells, the further out the application year the greater the inaccuracy of travel forecasts. The prime limitation of this study is with the single region source of the dataset used. Clearly, to generalize, the conclusions tests have to be done on data from several other regions.

APPENDIX A: Results of Analysis of Variance and Correlation Analysis Respectively

Analysis of Variance

Source	Partial Sum of Squares	Degrees of Freedom	Mean Square	F value	P value
Model	309730	82	3777	104.73	0.0000
Household Size	127687	18	7094	196.68	0.0000
Number of Motorcycles	623	3	208	5.76	0.0006
Number of Drivers	9537	8	1192	33.05	0.0000
Tenure	346	8	43	1.20	0.2942
Household Income	11669	14	833	23.11	0.0000
Dwell Type	491	11	45	1.24	0.2556
Number of Vehicles	1551	20	77	2.15	0.0021
Residual	682363	18919	36		
Total	992093	19001	52		
Number of Observations	19002				
R-squared	0.3122				

Correlation Matrix

	Household Size	Number of Motorcycles	Number of Drivers	Number of Vehicles	Household Income
Household Size	1				
Number of Motorcycles	0.0466	1			
Number of Drivers	0.4717	0.0955	1		
Number of Vehicles	0.2898	0.0460	0.5294	1	
Household Income	0.1426	0.0169	0.2920	0.2805	1

Acknowledgements

The authors would like to thank Charles Purvis of the San Francisco Bay Area Metropolitan Transportation Commission for providing data used in this study. Additionally, the first author conducted this research while at Tennessee Technological University.

References

Abdel-Aal, M.M. “Cross Classification Trip Production Model for the City of Alexandria.” *Alexandria Engineering Journal* 43 (2), (2004): 177-189.

Cotrus, A., J.N. Prashker, and Y. Shiftan. “Spatial and Temporal Transferability of Trip Generation Demand Models in Israel.” *Journal of Transportation and Statistics* 8 (1), (2003): 37-56.

Ewing, R., M. Deanna, and S. Li. “Land Use Impacts on Trip Generation Rates.” *Journal of the Transportation Research Board* 1518, (1996): 1–6.

Guevara, C. A. and A. Thomas. “Multiple Classification Analysis in Trip Production Models.” *Transport Policy* 14, (2007): 514-522.

Horton N.J. and K.P. Kleinman. "Much Ado About Nothing: A Comparison of Missing Data Methods and Software to Fit Incomplete Data Regression Models." *American Statistical Association* 61(1), (2007): 79-90.

Huisken, G. "Neural Networks and Fuzzy Logic to Improve Trip Generation Modeling." Paper presented at the 79th Annual Meeting of the Transportation Research Board, Washington, D.C., 2000.

Kikuchi, S. and J. Rhee. "Adjusting Trip Rate in the Cross-Classification Table by Using the Fuzzy Optimization Method." *Journal of the Transportation Research Board* 1836, (2003): 76–82.

Metropolitan Transportation Commission (MTC). "Trip Linking Procedures: 1990 Bay Area Household Travel Survey." Working Paper 2. Oakland, CA, Revised June 2003.

Muhammad S.B., I.G. Sehgal, and D. Laurence. "K-Ranked Covariance Based Missing Values Estimation for Microarray Data Classification." Proceedings of the 4th International Conference on Hybrid Intelligent Systems, Kitakyushu, Japan, December 5-8, 2004.

Ortuzar, J.D. and L.G.Willumsen. *Modelling Transport*. 3rd edition. John Willey and Sons, Inc., Chichester, England, 2001.

Purvis, C.L. "Changes in Regional Travel Characteristics and Travel Time Expenditures in the San Francisco Bay Area: 1960 – 1990." *Journal of the Transportation Research Board* 1466, (1994): 99–109.

Rengaraju, V. and M. Satyakumar. "Structuring Category Analysis Using Statistical Technique." *Journal of Transportation Engineering* 20 (6), (1994): 931-939.

Rengaraju, V. and M. Satyakumar. "Three-Dimensional Category Analysis Using Probabilistic Approach." *Journal of Transportation Engineering* 121(6), (1995): 538-543.

Retherford, R. D. and M.K. Choe. *Statistical Model for Causal Analysis.* John Wiley & Sons, New York, Inc., NY, 1993.

Rubin D.B. "Inference and Missing Data." *Biometrika* 63, (1976): 581–590.

Stopher, P.R. and K.G. McDonald. "Trip Generation by Cross-Classification: An Alternative Methodology." *Journal of the Transportation Research Board* 944, (1983): 84–91.

Transportation Research Board (TRB). "Metropolitan Travel Forecasting: Current Practice and Future Direction." Special Report 288, Washington, DC, 2007.

Walker, T. and H. Peng. "Long-Range Temporal Stability of Trip Generation Rates Based on Selected Cross-Classification Models in the Delaware Valley Region." *Journal of the Transportation Research Board* 1305, (1991): 61–71.

Wardman, M.R. and J.M. Preston. "Developing National Multi-modal Travel Models: A Case Study of the Journey to Work." Paper presented at the 9th World Conference on Transport Research, Seoul, South Korea, 2001.

Wayman J.C. "Multiple Imputation For Missing Data: What Is It And How Can I Use It?" Paper presented at the *2003 Annual Meeting of the American Educational Research Association*, Chicago, Illinois, 2003.

Zhao, H. "Comparison of Two Alternatives for Trip Generation." Paper presented at the 79th Annual Meeting of the Transportation Research Board, Washington, D.C., 2000.

Judith L. Mwakalonge *is an assistant professor in the civil and mechanical engineering technology department at South Carolina State University. Mwakalonge teaches and conducts research in transportation. Her primary research interests include travel demand modeling, model transferability, and traffic operations. Mwakalonge's current work explores the use of Radio Frequency Identification (RFID) and Bluetooth technologies in transportation and climate change as it relate to transportation. She received her Ph.D. degree in civil engineering from Tennessee Technological University.*

Daniel A. Badoe *is a professor in the department of civil and environmental engineering at Tennessee Technological University. He teaches undergraduate and graduate courses in transportation engineering and planning, and conducts research in the area of transportation data collection, travel behavior analysis, and travel demand modeling. He received his Ph.D. degree in civil engineering from the University of Toronto, Canada.*

Feasibility of an Intermodal Terminal in Rural Texas to Enhance Marketing and Transportation Efficiency

by Stephen Fuller, John Robinson, Francisco Fraire, and Sharada Vadali

This study examines the economic feasibility of investment in an intermodal terminal in west Texas and its implications for reducing roadway maintenance costs and CO_2 emissions. The study focuses on cotton, a leading agricultural commodity in Texas, which is highly dependent on the international market and truck transport from west Texas to the Dallas-Fort Worth complex for purposes of accessing containerized railroad transportation to West Coast ports. Analyses were accomplished with a spatial model of the U.S. cotton industry that features details regarding cotton handling, storage, and transportation activities. The analyses indicate an intermodal terminal in west Texas' intensive cotton-production region to be economically viable, attracting nearly 30% of Texas' average cotton production. Implementation of an intermodal terminal in west Texas would annually reduce truck travel on state roadways and lower pavement maintenance expenditure by approximately $1 million and reduce CO_2 emissions by 42% to 47%.

INTRODUCTION

This study examines the feasibility of investment in an intermodal terminal in west Texas and its implications for reducing roadway maintenance costs and CO_2 emissions. The study focuses on cotton, a leading agricultural commodity in Texas, which is highly dependent on the international market and on truck transport from west Texas to the Dallas-Fort Worth complex to access containerized railroad transportation to West Coast ports. Conceptually, an intermodal terminal in west Texas would allow cotton to access the intermodal system near its production location, removing the need for truck transport into the Dallas-Fort Worth metropolitan area. The assembly of cotton into the Dallas-Fort Worth railroad hub is at distances of up to 335 miles. Therefore, truck miles, roadway maintenance, and CO_2 emissions may be significantly decreased by the introduction of an intermodal terminal in west Texas, the locus for Texas' cotton production.

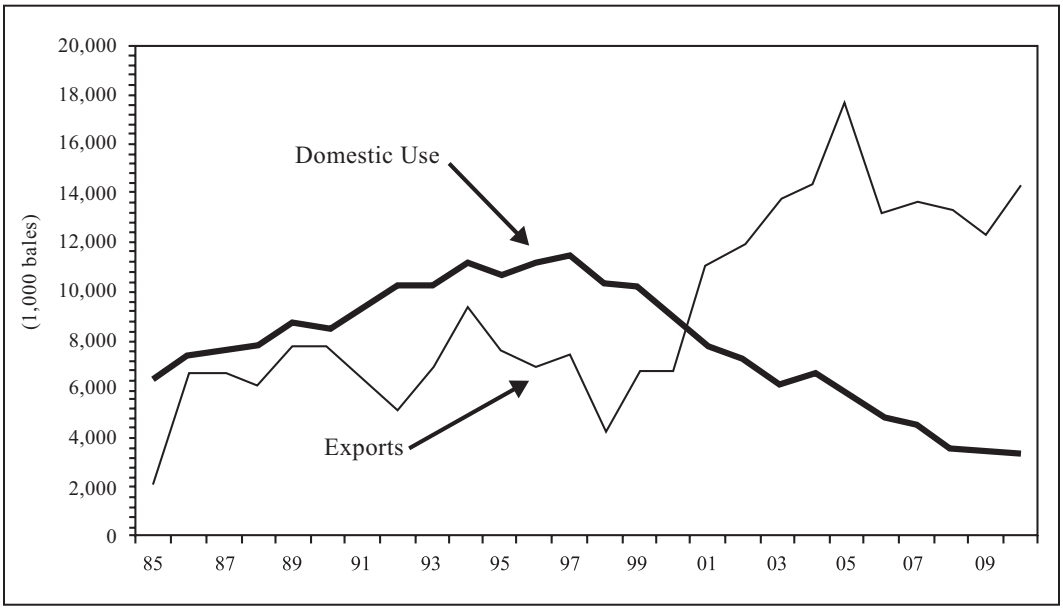
The objectives of this study are to (1) determine the economic feasibility of an intermodal terminal in the intensive cotton-production region of west Texas and evaluate the sensitivity of the intermodal terminal's feasibility to selected exogenous forces, (2) estimate reduced roadway maintenance expenditure resulting from investment in the terminal, and (3) estimate reduction in CO_2 emissions associated with the intermodal terminal and the value of the reduced emissions.

Many of the analyses were accomplished with a spatial model of the U.S. cotton industry that features cotton handling, storage, and transport activities that link cotton gins to warehouses and ultimately to intermodal terminals, domestic textile mills, U.S. port areas, and border-crossing locations.

BACKGROUND

The transport and logistics system serving the U.S. cotton industry has undergone important changes as a result of the demise of the domestic textile industry and the corresponding growth in cotton exports. Currently, exports comprise nearly 80% of annual cotton disappearance (Figure 1).

Figure 1: Domestic U.S. Cotton Use and U.S. Exports 1985/86–2010/11



Source: U.S. Department of Agriculture (2010)

Cotton that had historically been transported by truck and railcar to southeast U.S. textile mills is now largely routed to export via the U.S. West Coast, Gulf of Mexico, southeast ports, and the Mexican border. Fuller, Park and Robinson (2007) show Texas, the leading cotton-producing state, ships the majority of its export-destined cotton to West Coast ports (Long Beach/Los Angeles). Nationally, about 48% of U.S. cotton is exported via West Coast ports, with the Gulf of Mexico and East Coast ports handling about 17% and 16%, respectively, and border-crossing locations accommodating about 19% of exports (WISERtrade 2009). All cotton exported from U.S. ports is in marine containers, and because of unequal trade flows between Asia and the United States, considerable U.S. cotton is backhauled in containers to Asian textile mills. Unfortunately, the intense cotton-producing regions in Texas are geographically remote and cannot efficiently access the westward flow of empty containers to West Coast ports.

REVIEW OF LITERATURE

A review of literature indicated few efforts to construct spatial models of the U.S. cotton industry. However, spatial equilibrium models of the international grain economy have been successively employed by Fellin, Fuller, Kruse, Meyers, and Womack (2008), and Wilson, Dahl, Taylor, and Woo (2007) to analyze grain transportation issues. These models will serve as a prototype for the spatial cotton model constructed for this study.

The economic feasibility of an intermodal terminal was previously examined by the Upper Great Plains Transportation Institute (2007), which investigated a terminal featuring container/trailer intermodal services in rural Minnesota and North Dakota. Vachal and Berwick (2008) examined the feasibility of using a container-on-barge facility to export Illinois grain to Asia, and the Minnesota Department of Agriculture and Wilbur Smith Associates (2008) examined the feasibility of investments in intermodal terminals on short-line and regional railroads in the Midwest.

The west Texas intermodal terminal investigated in this study is expected to reduce roadway maintenance cost since cotton will enter the intermodal stream near its production area rather than routed to distant intermodal facilities in Dallas-Ft. Worth. Therefore, there is interest in examining

previous studies that measure road maintenance costs. The Washington State Department of Transportation (2003) estimated increased road maintenance costs resulting from abandonment of a railroad in eastern Washington, and related studies by Babcock, Bunch, Sanderson, and Witt (2003a, 2003b) estimated road damage costs resulting from the proposed abandonment of short-line railroads serving Kansas using a pavement-damage model by Tolliver and HDR Engineering, Inc. (2000). Warner and Terra (2006) estimated the reduction in pavement damage to Texas roadways that result from the operation of the state's short-line railroads using a method outlined by Bitzan and Tolliver (2001). They estimated pavement damage to rural interstate highways was 12.7 cents per truck-mile, while the pavement damage to rural major collectors was estimated at 30.5 cents per truck-mile. After considering federal and state fuel taxes paid by trucks, the uncompensated road damage was estimated at 5.03 cents per truck-mile for rural interstate highways and 22.83 cents per truck-mile on rural major collectors.

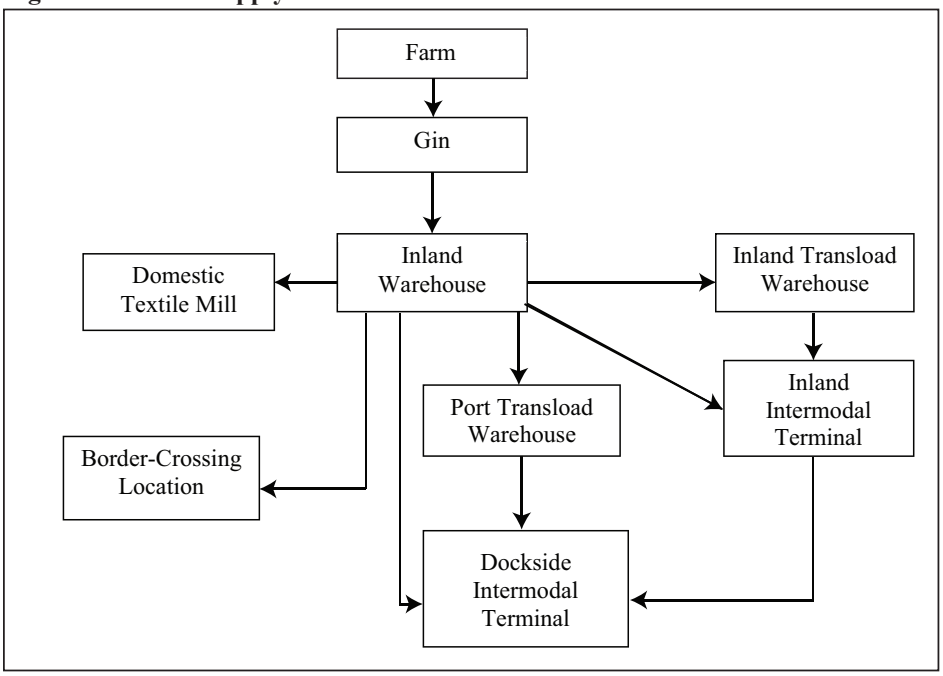
Andrieu and Weiss (2008) review methods and tools available for the measurement of CO_2 for major transport modes under alternative operating conditions and, following the approach by McKinnon (2007), show how the calculated emission parameters may be adjusted to reflect the truck's capacity utilization (backhaul frequency). The EPA's Office of Transportation and Air Quality (EPA 2010) recently developed a modeling system titled the *Motor Vehicle Emissions Simulator* (MOVES), which estimates emissions from cars, trucks, and motorcycles. It shows the average atmospheric emission rates for Class 8 trucks (heavy-duty trucks) is about 2,000 grams of CO_2 per mile at average speeds of 50 to 60 miles per hour. In addition, analysis shows that emissions are affected by truck capacity utilization (backhaul frequency) through its impact on fuel use. Franzese, Knee, and Slezak (2009) estimate the effect of load size (frequency of empty haul) on fuel efficiency of Class 8 trucks, and the analyses suggest the reasonableness of the rule of thumb "each additional 10,000 pounds of payload decreases fuel economy about 5%." The Federal Railroad Administration (USDOT 2009) provides a comparative evaluation of rail and truck fuel efficiency for 23 competing moves. Eleven of the moves compared fuel efficiency of trucks with double-stack container cars for moves ranging from 294 to 2,232 miles, with results indicating rail transport was 2.2 to 5.5 times more fuel efficient than trucks.

MODEL

The cotton spatial model developed for this study is a cost-minimizing, transshipment model that links gins, warehouses, domestic textile mill regions, inland intermodal terminals, and U.S. ports and border-crossing locations (Figure 2). Although farms are included in Figure 2, the cotton supply chain represented in the developed model originates at gins since farm-level supplies have no direct bearing on study objectives. New-crop cotton supply in the spatial model is generated in the first quarter of the crop year at gins while the carry-in stocks from the previous year are largely held at inland warehouses. Cotton gins ship new crop production by truck (flatbed/van) to nearby inland warehouses.

Inland warehouses ship to domestic mills, border-crossing export locations (Canada, Mexico), inland transload warehouses, inland intermodal terminals, port transload warehouses, and dockside intermodal terminals (Figure 2). Transload warehouses (inland, port) typically receive cotton by truck (flatbed/vans) and then place it into containers, which are drayed to nearby intermodal terminals (inland, dockside). If the inland warehouse has loaded a container, chassis, and truck combination, it may be directly transported to an inland intermodal terminal where it is loaded to a double-stack car for transport to a dockside intermodal terminal, or the container of cotton may be transported directly to a dockside intermodal terminal for loading to a container ship (Figure 2). Truck transportation dominates except for links between inland intermodal terminals, and dockside intermodal terminals which involve the containerized rail movements, and on selected routes between inland warehouses and ports and border-crossing locations where rail transport (boxcar)

Figure 2: Cotton Supply Chain



has a limited role. Trucking and rail linkages in the developed model are without constraints since cotton haulage was small as compared with all transport activity.

In the developed model, domestic cotton demands are fixed in U.S. demand regions (domestic textile mill), and foreign demands are fixed at U.S. ports and border-crossing locations (Figure 2). Cotton handling and storage costs in the model are incurred at inland and transload warehouses, while handling costs are incurred at all intermodal facilities, ports, and border-crossing locations. Plant capacity constraints are included for each gin and inland and transload warehouse; however, intermodal terminals (inland, dockside) and border crossings have no capacity constraints since cotton is a small portion of total volume at these sites (Figure 2).

Table 1 includes the definition of subscripts, parameters, and variables in the following mathematical description of the cost-minimizing, transshipment model:

(1) Objective function:

$$Min \sum_i \sum_w \sum_t c_{iw} X_{iwt} + \sum_w \sum_n \sum_s \sum_t c_{wnst} X_{wnst} + \sum_w \sum_l \sum_t c_{wlt} X_{wlt} + \sum_w \sum_k \sum_s \sum_t c_{wkst} X_{wkst} + \sum_j \sum_m \sum_s \sum_t c_{jmst} X_{jmst} + \sum_k \sum_n \sum_t c_{kn} X_{knt} + \sum_w \sum_t cs_w H_{wt}$$

(2) Quarterly demand constraints:

2a. $\sum_w \sum_s X_{wnst} + \sum_k X_{knt} \geq D_{nt}$, *for all n, t .*

2b. $\sum_w \sum_{wlt} \geq D_{lt}$, *for all l, t .*

2c. $[(\sum_{it} S_{it} + \sum_w H_{w0}) - (\sum_n \sum_t D_{nt} + \sum_l \sum_t D_{lt})] \cdot \gamma_u \leq \sum v \in \sum_j \delta_v H_{j4}$, *for all u.*

(3) Quarterly supply constraints:

$\sum_w X_{iwt} \leq S_{it}$, *for all i, t.*

(4) Warehouse shipment balance constraint:

$$\sum_n \sum_s X_{jnst} + \sum_l X_{jlt} + \sum_k \sum_s X_{jkst} + \sum_m \sum_s X_{jmst} + H_{jt} - H_{j,t-1} \leq \sum_i X_{ijt}, \quad for\ all\ t\ and\ j \subset w.$$

(5) Transloading warehouse balance constraint:

$$\sum_n \sum_s X_{mnst} + \sum_l X_{mlt} + \sum_k \sum_s X_{mkst} + H_{mt} - H_{m,t-1} - \sum_j \sum_s X_{jmst} \leq \sum_i X_{imt}, \quad for\ all\ t\ and\ m \subset w.$$

(6) Quarterly intermodal terminal shipment balance constraints:

$$\sum_n X_{knt} \leq \sum_w \sum_s X_{wkst}, \quad for\ all\ k,\ t\ .$$

(7) Quarterly warehouse storage capacity constraints:

$$H_{wt} \leq Capacity_{wt}, \quad for\ all\ w,\ t\ .$$

(8) Non-negativity constraint:

$$X_{iwt}, X_{wnst}, X_{wlt}, X_{wkst}, X_{jmst}, X_{knt}, H_{w,t} \geq 0, \quad for\ all\ i, j, k, l, m, n, s, t\ .$$

Table 1: Subscripts, Parameters and Variables in Formulated Model

Subscripts:	
t	Quarter (Q1, Q2, Q3, Q4)
i	U.S. excess supply location (i = 1, 2, 3, ..., 811)
l	U.S. excess demand locations (l = 1, 2, 3, ..., 11)
w, j, m	Originating warehouses (w = 1, 2, 3, ..., 415) *j* are originating warehouses that may not transload *m* are transloading facilities
k	Inland intermodal terminals (k=1, 2, 3, 4)
n	U.S. ports and border crossings (n = 1, 2, 3, ..., 17)
s	Inland modes of transportation (s = 1, 2, ..., 5)
u	U.S. regions (u = 1, 2, 3, 4)
v	U.S. states (v = 1, 2, 3 ..., 17)
Parameters:	
C	Transportation and handling cost per metric ton for truck, railroad, and ship modes as appropriate
CS	Storage cost per metric ton
$Capacity_{wt}$	Maximum storage capacity at warehouse *w* in quarter *t*
δ_v	Indicator variable for state *v* ($\delta = \{0,1\}$)
γ_u	Final quarter storage for region *u*
Variables:	
S_{it}	U.S. excess supply in quarter *t* at location *i*
D_n	Excess demand at U.S. port *n* (foreign excess demand)
D_l	Excess demand at U.S. mill *l*
H_{wt}	Storage in quarter *t* at warehouse *w*
X	Cotton flow in metric tons between nodes

Equation 1 minimizes the costs (C) associated with handling, storage (*H*), and transportation (*X*) of baled cotton that originates at U.S. gins over the four quarters of a crop year that extends from August 1 through July 31. The letter *t* identifies the quarter, where *t* = Q1 corresponds to the initial quarter of the crop year when harvest commences.

The model allows cotton to be routed from gins (*i*=811) to inland warehouses (*w*=415) and then, for export-destined cotton, to transloading warehouses (*m*=37) and inland intermodal terminals (*k*=4), before arriving at ports and border crossings (*n*=17).

Further, the model allows for direct shipment from inland warehouses to domestic mill demand regions (*l*=11), and to ports and border crossings (*n*=17). Cotton can be transported via five transportation alternatives (*s*=5). Railroad boxcar and intermodal (containers) shipments are included on selected corridors, while three truck assembly alternatives are included. The trucking possibilities include (1) truck, chassis, container combination (source-loaded) (2) flatbed/van shipments and (3) flatbed/van shipments with backhauls on selected routes. All transportation arcs are without constraints. Lastly, storage in inland warehouses and transloading warehouses is allowed in all four quarters.

Equation 2a is a demand constraint requiring the shipment of predetermined quantities per quarter to ports and border crossings (*n*), while Equation 2b is a constraint requiring predetermined quantities per quarter to domestic mill demand regions (*l*=11). The third demand equation (Equation 2c) specifies the ending stocks ($H_{j,4}$) in four regions (*u*). These regions are the mid-south, southeast, southwest, and west. Each region contains several states *(v)*. Therefore, given that $d_v = 1$ when state *s* belongs to region *u,* and zero otherwise, the equation distributes the excess supply into the model according to the proportions specified by g_u, while allowing each warehouse's storage of cotton to be determined endogenously.

Equation 3 describes a gin plant's maximum output of baled cotton.

The inland warehouse and the transload warehouse represent two types of warehouses ($w = j + m$), whose distinction is their ability to receive (*m*) or not receive (*j*) baled cotton shipments from other warehouses. Inland warehouses are located in proximity to cotton production and receive cotton from area gins. Transloading warehouses receive from inland warehouses and gins. Transloading warehouses in proximity of inland intermodal terminals are inland transload warehouses (Figure 2), while those near a port are identifed as port transloading warehouses. Equation 4 constrains the sum of quarterly shipments from inland warehouses to intermodal terminals (*k*), transloading terminals (*m*), ports (*n*), and mills (*l*), and constrains storage for the next period (H_t) to be no more than the incoming new-crop quarterly supplies (X_{ijt}) plus carry-in storage stock (H_{t-1}), where $H_{j,0}$ refers to the stocks carried in from the previous year.

Equations 5 and 6 are similarly interpreted for the transloading warehouses and intermodal terminals, respectively. The transloading warehouses are a subset of the regular warehouses. Thus, Equation 5 applies only to the transloading warehouses and is in place of Equation 4. Equation 7 constrains the quarterly storage in warehouses to not exceed their capacity, and equation 8 is the standard non-negativity constraint in linear programming.

The specified model includes 811 gins and 415 originating warehouses located in 17 states (Alabama, Arizona, Arkansas, California, Florida, Georgia, Kansas, Louisiana, Mississippi, Missouri, New Mexico, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia). Four major intermodal terminals serve the cotton industry, and these include Memphis, Dallas, Houston, and Lubbock. The Lubbock operation is currently privately operated, comparatively small, and available to few cotton shippers. The analysis focuses on construction of an intermodal terminal in Lubbock that is capable of accommodating all area shippers seeking its service. Trade sources indicate the current Lubbock operation would close if a modern facility were available.

Thirty-seven transloading warehouses operate in the inland intermodal terminal centers and receive truck-delivered cotton (flatbed/van) from originating warehouses and gins. In addition, inland intermodal terminals operate in conjunction with selected port areas that receive containers

of rail-transported cotton from these terminals. The dockside intermodal terminals that receive rail-transported cotton are at the following locations: California (Los Angeles/Long Beach and San Francisco), Georgia (Savannah), Louisiana (New Orleans), South Carolina (Charleston), Texas (Galveston/Houston), Washington (Seattle), and Virginia (Norfolk). Additional ports are located in Alabama (Mobile), Florida (Everglades/Jacksonville), Mississippi (Gulfport), and Texas (Freeport).

All ports in the model feature a transload warehouse that receives truck-transported (flatbed/van) cotton, which is placed in containers and drayed to dockside. In addition, all dockside intermodal terminals may receive source-loaded cotton (containers) that is truck transported from inland warehouses. Border-crossing locations are in Michigan (Detroit), New York (Buffalo), and Texas (Laredo/Harlingen). Eleven domestic mill demand regions are included in the following states: Alabama (two), Georgia (two), North Carolina (two), South Carolina (two), Tennessee (one), Texas (one), and Virginia (one).

Because truck transport is central to the marketing of U.S. cotton, several truck assembly systems are featured in the model. Trucks (flatbeds/vans) assemble baled cotton from gins to inland and transloading warehouses and are central to the shipment of cotton from inland warehouses. Trucks (flatbeds/vans) ship from inland warehouses to domestic mill demand locations, border-crossing sites, and transloading warehouses at inland and dockside intermodal terminal locations. The transloading warehouses receive truckloads of cotton, which are placed into containers and drayed to intermodal terminals (inland and dockside). The containerized cotton received at inland intermodal terminals is subsequently rail transported (double-stack cars) to dockside, and similarly containerized cotton exiting a port transload warehouse is drayed to dockside for export.

An additional truck assembly system involves a truck, chassis, and container combination (source-loaded), which travels to an inland cotton warehouse where the container is loaded and then transported to an inland intermodal terminal for loading aboard a container car for shipment to a port area. Similarly, truck, chassis, and container (source-loaded) may transport cotton from inland cotton warehouses to dockside. The assembly system involving truck, chassis, and container (source-loaded) removes the need to transship cotton through transloading warehouses, which reduces handling and associated drayage charges.

The model also features a truck assembly system (flatbed/van) that includes truck-backhaul opportunities for cotton moving from inland warehouses in west Texas and Oklahoma to transloading warehouses in the Dallas-Fort Worth intermodal terminal market areas and the Houston and Galveston port areas.

Intermodal transport is central to the movement of cotton to West Coast ports and, to a lesser extent, to East Coast ports. Railroad boxcars are used to transport small quantities from selected inland warehouses to ports and border crossings.

DATA

The following discussion regarding cotton supply and warehousing and the transportation and logistics network relates to data incorporated into the spatial model, while discussion pertaining to intermodal terminal investments and costs, roadway pavement costs, and CO_2 emissions offers insight on data used in combination with the spatial model to accomplish study objectives.

Cotton Supply and Warehousing

The annual production of baled cotton was generated at the spatial model's gin plant sites based on plant capacity and cotton production in the crop reporting district where the gin plant was located. Carry-in cotton stocks were created at each warehouse based on regional carry-in stock data and warehouse storage capacity. In particular, a gin plant's annual output was determined by allocating a crop reporting district's production to area gin plants based on plant capacity. Temporal output

of baled cotton at cotton-gin plants was based on data from the regional cotton classing offices. A state's carry-in cotton stocks were distributed among state warehouses based on each warehouse's storage capacity and Intercontinental Exchange (ICE) (2009) data on stored cotton at cotton-futures delivery points.

The gin plant population came from the Cotton Board (2009), and proprietary information on historical gin plant capacity and output was obtained from a national cotton industry organization. The temporal ginning pattern in each production region was approximated with the USDA's (2009c) Agricultural Marketing Service cotton classing office data. Cotton production data by crop reporting district were from the USDA's (2009d) National Agricultural Statistical Service, while the USDA's (2009b) Farm Service Agency was the source of information on the cotton warehouse population and associated warehouse capacity. Data on carry-in cotton stocks were available from the U.S. Census Bureau (2009b), the USDA's (2009a) Economic Research Service *Cotton and Wool Yearbook 2009*, and the Intercontinental Exchange's (2009) *Cotton Certified Stock Report*. The Census Bureau's cotton carry-in stocks data by state were adjusted to reflect the USDA's national carry-in estimate. In addition, the Intercontinental Exchange's data on cotton storage stocks in each of the five cotton-futures delivery markets (Galveston and Houston, Texas; Greenville, South Carolina; Memphis, Tennessee; and New Orleans, Louisiana) were used to allocate carry-in stocks among delivery-point warehouses based on the storage capacity in each delivery market. A state's remaining cotton carry-in stocks were allocated among warehouses outside of the futures-market delivery locations based on storage capacity. Individual cotton warehouse handling and storage charges were obtained from a survey of Texas warehouses, Fuller et al. (2007), the Texas Cotton Association (2009), warehouse websites, and a proprietary list constructed by a national cotton industry organization.

Estimates of domestic cotton-mill demand by state were obtained from the U.S. Census Bureau's (2009a) *Current Industrial Reports* on cotton consumption. Employment at broad-woven fabric mills and yarn-spinning mills was used to estimate cotton use for the 11 sub-state domestic demand regions. Employment at U.S. broad-woven fabric and yarn-spinning mills were taken from Manta (2009a, 2009b). Cotton exports via individual ports and border-crossing locations were from WISERtrade (2009).

Transportation and Logistics Network

Truck brokers, freight forwarders, and selected cotton merchants provided information on truck rates connecting warehouses to ports, domestic mills, transload facilities, and intermodal terminals. Information on cotton trucking rates that link gin plants to warehouses was obtained by a telephone survey of 263 Texas, Oklahoma, New Mexico, and Kansas cotton gin plant operators in 2008 and 2009. These data were used to estimate truck rate equations explained by distance of haul where distance was determined by the route that minimized the trucker's drive time, binary variables that accounted for geographic region and distance zones. Further, with scalars provided by industry personnel, the base truck rates—obtained from the estimated rate equations and the drayage charges—were adjusted to reflect fuel surcharges that were based on the U.S. Department of Energy's (USDOE) (2009) *Monthly Retail On-Highway Diesel Prices* for nine U.S. regions. The regional diesel price information yielded truck rates and drayage charges that differed by U.S. region. See Fuller, Robinson, Fraire, and Vadali (2011) for estimated truck rate equations.

Railroad rate and routing data were obtained from the Surface Transportation Board's (STB) (2009) *Public Use Waybill*, selected cotton merchants, freight forwarders, and railroad company personnel. Waybill data on cotton shipments were sparse and generally inadequate to estimate rate equations, however, it provided insight on ranges of rates by shipping location, and with counsel from cotton merchants and railroad industry personnel, representative values were obtained. Some warehouses in the mid-south and Texas plains shipped small quantities of cotton by boxcar to Gulf ports and U.S.-Mexico border-crossing locations. In contrast, large quantities of containerized

cotton were shipped from selected inland intermodal terminals (e.g., Memphis, Dallas-Ft. Worth) to West Coast ports. Typically, intermodal (containerized) shipments were shipped via multicar arrangements and unit trains while boxcar shipments included two cars or less.

Intermodal Terminal Investment and Costs

Based on a survey of Texas cotton warehouses (Fuller et al. 2007) regarding shipments to various destinations and on regional cotton-production trends, investment levels and costs were estimated for intermodal terminals that shipped 12,000, 14,000, 16,000, or 18,000 containers of cotton per year. Each 40-foot marine container (FEU) holds 88 cotton bales. Information on terminal investment levels and costs were used to estimate a cost-volume model for each terminal size.

Estimated terminal dimensions, terminal investment requirements, and costs were largely based on previous studies. Stewart, Ogard, and Harder (2004) examined intermodal terminal requirements in small and medium-size communities and offered parameters useful in prescribing terminal yard dimensions and associated railroad track. A study by the Michigan Department of Transportation and U.S. Department of Transportation (2008) provided insight on type and number of rail turnouts and costs, as well as information on container parking. Loading space requirements came from the Victoria Transport Policy Institute (2008). Personnel from Wilbur Smith Associates offered information on requirements regarding terminal lighting, lifters, tractors, chassis, and employees based on previous study efforts. Estimated land costs for an intermodal terminal came from the website of the Lubbock Economic Development Alliance (2008), while a study by the Minnesota Department of Agriculture and Wilbur Smith Associates (2008) provided information on investment in truck scales, utilities, lifters, tractors, and chassis. Estimated investment in the 12,000-, 14,000-, 16,000-, and 18,000-container-per-year terminals were $7.92, $8.82, $9.79, and $10.69 million, respectively (Fuller et al. 2011).

The estimation of depreciation expense, insurance expense, maintenance and repair costs, energy costs, and taxes was partially based on a study by Berwick (2007) of the Upper Great Plains Transportation Institute, who researched intermodal terminals in rural areas and offered insight on computation methods to estimate these costs. Based on the Berwick (2007) study and with selected computational adjustments for location and time period, the annual costs were estimated for the four intermodal terminal sizes. Annual fixed costs for the 12,000-, 14,000-, 16,000-, and 18,000-container-per-year terminals were estimated to be $2.11, $2.35, $2.61, and $2.85 million, respectively. When the terminals were operating at capacity, the estimated operating costs were $0.86, $0.91, $1.02, and $1.07 million, respectively. Total cost per handled container ranged from $248 or $2.81 per bale for the 12,000-container terminal to $218 per container or $2.48 per bale for the 18,000-container terminal (Fuller et al. 2011).

Roadway Pavement Cost

To estimate the effect on total pavement costs of introducing an intermodal terminal into the west Texas cotton marketing system, the loaded truck-miles *ex ante* and *ex post* the new terminal were calculated with the spatial model. Then these data in combination with marginal pavement cost parameters per loaded truck-mile were converted into total pavement cost estimates.

Pavement cost estimation required use of the Federal Highway Administration's (FHWA) functional roadway classification guidelines (USDOT 2000a) to approximate miles traveled over each functional system and updated marginal pavement cost parameters for each functional roadway classification. Marginal pavement cost for the rural interstate highway (12.7 cents for an 80,000-pound, five-axle truck) was taken from FHWA's *Federal Highway Cost Allocation Study* (USDOT 1997). Dr. Denver Tolliver of the Upper Great Plains Transportation Institute provided previous estimates of pavement costs for principal and minor arterials and collectors. The collected

pavement costs were subsequently updated with FHWA's *Construction Cost Trends for Highways, Table PT-1* (USDOT 2010) and FHWA's *Price Trends for Federal-Aid Highway Construction* (USDOT 2006*)*. After consideration of federal and state fuel taxes (44.4 cents per gallon) and an estimated 5.5-miles-per-gallon fuel efficiency, the uncompensated marginal costs per loaded truck-mile were estimated for an 80,000-pound, five-axle truck operating on interstate ($0.059), principal arterial ($0.259), minor arterial ($0.359), and collector ($0.876) roadways.

CO_2 Emissions

The anticipated reduction in CO_2 emissions that result from introducing a new intermodal terminal in west Texas was estimated by contrasting truck mileages obtained from spatial model solutions *ex ante* and *ex post* the new facility in combination with CO_2 emission per truck-mile. In particular, truck mileages from these solutions in combination with CO_2 emissions per loaded and empty truck-mile were used to estimate total emissions *ex ante* and *ex post* the new terminal.

The Center for Air Quality Studies at the Texas Transportation Institute provided a per-mile CO_2 emission rate for loaded Class 8 trucks operating at average speeds: the emission rate was estimated with MOVES 2010 (EPA 2010). At an assumed average speed of 55 miles per hour, the Class 8 truck has a CO_2 emission rate of 2,003.7 grams per loaded mile. For empty truck mileage, the emission rate was adjusted downward in proportion to reduced fuel consumption. Franzese et al. (2009) analyses indicate the reasonableness of the rule of thumb "that each additional 10,000 pounds of payload decreases fuel economy about 5%." Further, the Federal Railroad Administration's *Comparative Evaluation of Rail and Truck Fuel Efficiency in Competitive Corridors* (USDOT 2009) indicate the reasonableness of this rule of thumb. Based on these data, the CO_2 emission rate per loaded truck-mile was estimated to be 2,003.7 grams, and the rate per empty truck-mile was 1,615.8 grams.

Important quantities of cotton that involve a truck, chassis, and container (source-loaded) are transported from west Texas to Dallas-Fort Worth terminals. Typically, the container is empty when departing the intermodal terminal; therefore, for all CO_2 computations, it was assumed that one-half of the round-trip mileage associated with source-loaded cotton involves empty truck-miles. Further, based on information from a truck broker, it was assumed that all truck-transported cotton moving via van/flatbed into Dallas-Fort Worth involved a backhaul percentage of 50%.

Introduction of an intermodal terminal in west Texas will require the railroad to reposition empty containers from the Dallas-Fort Worth complex to the west Texas terminal. The net effect of this activity is assumed to be neutral regarding railroad's CO_2 emissions. *Ex ante* the west Texas terminal, truck-transported west Texas cotton would be routed to Dallas-Fort Worth and placed in containers for shipment to West Coast ports. This containerized cotton will pass through west Texas on its route to West Coast ports. *Ex post* the west Texas facility, empty containers will be routed by railroad to west Texas and then loaded for shipment to West Coast ports. Thus, the affected mileage that the rail-transported container travels is little altered by introduction of an intermodal terminal. Therefore, it was assumed that railroad CO_2 emissions would not be significantly affected by the introduction of an intermodal terminal in west Texas.

RESULTS

Feasibility of Intermodal Terminal

Initial analyses with the spatial model focused on determining total revenues and associated volumes resulting from alternative per-bale charges by the new or hypothetical intermodal terminal in Lubbock. This process was designed to determine feasibility of various per bale charges that might be levied by the hypothetical terminal and its associated total revenues. After determination

of an attractive per-bale charge, a linear total revenue equation was generated for the hypothetical terminal. The total revenue equation in combination with the linear total cost equation (fixed and variable costs) for each of the four intermodal terminal sizes was used to determine the break-even output and profitability for each terminal size. No constraints relating to terminal size were placed into the spatial model when identifying attractive per-bale charges that might be levied by the new facility. Further, there was no need to segregate the effect of the current intermodal operator since trade sources indicated the current facility would close with the opening of the hypothetical facility.

The least-cost spatial model projected that 3.57 million bales would be assembled to the hypothetical intermodal terminal if $1 per bale were charged above all costs and when the charge was increased to $2, $3, $4, and $5 per bale the associated terminal volume declined to 3.08, 2.58, 2.02, and 0.538 million bales, respectively. These analyses show a $4 per-bale charge ($352 per container) would generate the greatest intermodal terminal revenue ($4 per bale × 2.02 million bales = $8.08 million).

The developed linear cost-volume model for the 12,000-, 14,000-, 16,000-, and 18,000-container terminals in combination with the $4 per-bale revenue was used to identify terminal profitability and break-even volumes. The estimated break-even volume for the 12,000-, 14,000-, 16,000-, and 18,000-container terminals was 7,539, 8,211, 9,061, and 9,758 containers per year, respectively (Table 2). All containers are assumed to be 40-foot marine containers (FEU), which hold 88 bales. When the terminal operates at capacity, the expected annual returns above specified costs for the four analyzed terminals (12,000-, 14,000-, 16,000-, and 18,000-container terminals) are an estimated $1.25, $1.66, $2.00, and $2.41 million, respectively, and the estimated rates of return on investment were 15.8%, 18.8%, 20.4%, and 22.5% (Table 2). Rates of return were estimated by dividing returns above specified costs (Table 2) for each size of container terminal by its associated investment and multiplying the resulting value by 100. Rate of return calculations were as follows for each respective intermodal terminal ($ values in millions): $1.25/$7.92 = 15.8%; $1.66/$8.82 = 18.8%; $2.00/$9.79 = 20.4%; $2.41/$10.70 = 22.5%.

Table 2: Estimated Annual Revenues and Costs for 12,000-, 14,000-, 16,000-, and 18,000-Containers-per-Year Intermodal Terminal Operating in Lubbock, Texas

	Containers per Year (FEU) 12,000	Container per Year (FEU) 14,000	Container per Year (FEU) 16,000	Containers per Year (FEU) 18,000
Fixed Cost ($)	2,113,466	2,354,044	2,613,110	2,853,593
Management, Employee, and Other Expenses ($)	860,080	914,001	1,017,978	1,072,030
Total Cost ($)	2,973,546	3,268,045	3,631,088	3,925,623
Total Revenue ($)	4,224,000	4,928,000	5,632,000	6,336,000
Break-Even Volume (Containers)	7,539	8,211	9,061	9,758
Returns above Specified Costs ($)	1,250,454	1,659,955	2,000,912	2,410,377
Rates of Return on Investment (%)	15.8	18.8	20.4	22.5

Sensitivity of Intermodal Terminal's Feasibility to Selected Exogenous Forces

Low and high regional cotton-production levels were included in the spatial model to evaluate the effect on the feasibility of the hypothetical intermodal terminal. The analysis shows that at the high production levels of 2005 and 2007 (7.0 million bales), the Lubbock terminal would attract 2.66 million bales, whereas at the low production level of 2.54 million bales (2000 production), approximately 1.7 million bales would transit the Lubbock terminal. These analyses indicate the largest of the examined intermodal terminals (18,000 containers per year or 1.58 million bales) would have ample cotton supplies to operate at full capacity in all years during 2000–2009.

Additional analysis was carried out to determine if operation of an existing intermodal terminal in Amarillo, Texas, as a cotton shipping center would unfavorably affect the economic feasibility of the hypothetical Lubbock terminal. Amarillo is approximately 120 miles north of Lubbock and is at an extended distance from the intensive cotton-production area surrounding Lubbock. Further, in contrast to Lubbock, Amarillo has modest cotton warehouse capacity and associated cotton marketing infrastructure. Regardless, USDA's Farm Service Agency showed one large cotton warehouse to operate in Amarillo (USDA 2009b). Further, Amarillo is located on the Burlington Northern (BNSF) railroad line that connects the Chicago area to southern California, a route that transports empty containers from the Midwest to California; therefore, a possible opportunity to efficiently route empty containers into the Amarillo terminal.

The spatial model featuring the hypothetical intermodal terminal in Lubbock was modified to allow assembly of cotton to Amarillo from area gins and warehouses and its shipment to West Coast ports. The modified model reflected flatbed/van costs of trucking into an Amarillo transloading warehouse and associated drayage charges to the Amarillo intermodal terminal as well as a source-loaded assembly system involving truck, container, and chassis. Further, the modified model included a charge by the Amarillo terminal for container handling and lifts, and an estimated railroad rate to West Coast ports.

Analysis showed operation of the Amarillo intermodal facility as a cotton shipping site has negative implications for investment in the hypothetical Lubbock terminal. If the source-loaded assembly system (truck, container, and chassis) operating around Lubbock and Amarillo was limited to a distance of 50 miles and the flatbed/van system was without distance restrictions, the Lubbock intermodal terminal volume would decline modestly to 1.9 million bales from 2.02 million bales ($4 per-bale charge), with an estimated quantity through Amarillo of 0.147 million bales. However, if Amarillo and Lubbock had a source-loaded assembly system operating at a distance of 100 miles, Lubbock's hypothetical intermodal terminal would experience a precipitous loss in volume, handling an estimated 0.76 million bales, while the Amarillo terminal would increase to 1.69 million bales. Therefore, the investment required to construct and operate the hypothetical facility in Lubbock places it at a competitive disadvantage to the existing intermodal terminal in Amarillo.

Many agricultural crop producers, including cotton producers, participate in federal commodity programs. Removal of these commodity programs could influence west Texas cotton production and the feasibility of the hypothetical intermodal terminal in Lubbock. An investigation of this concern showed that flexibility provisions of recent farm legislation and high cotton prices since 2008 have reduced the influence of selected federal subsidies. However, federally subsidized crop insurance has in recent years been a major determinant of cotton plantings in the study area. If this program were curtailed, riskier dry land cotton production may exit the production region and unfavorably affect the feasibility of the intermodal terminal.

Effect of Intermodal Terminal on Annual Roadway Pavement Costs

By contrasting spatial model solutions representing the current cotton marketing system and a marketing system featuring the hypothetical terminal, it was possible to estimate how truck routes

and loaded truck-miles would be affected by the new facility. Unfortunately, measurement of truck routes and loaded truck-miles associated with the current cotton transportation system was complicated by the small intermodal operator in Lubbock who ships an unknown number of bales per year to the West Coast. Trade sources indicate the private intermodal operation annually ships from 500,000 to 750,000 cotton bales from Lubbock to West Coast ports. Therefore, the current cotton marketing system was represented by two spatial model solutions where one solution featured a Lubbock volume constraint of 500,000 bales and the other a 750,000 bale constraint. This approach yields a range of truck-miles associated with the current marketing system and, therefore, a range of saving associated with the hypothetical terminal.

The two spatial model solutions representing the current cotton marketing system were perused to obtain all origin-destination combinations for truck haulage between involved cotton warehouses and terminals. Next, a routing code was used to record the routes between these facilities from which mileages traveled via interstate, principal arterial, minor arterial, and collector roadways were measured. Although the portion of miles traveled via each functional roadway classification varied, principal arterials and interstates were the primary roadway carriers (85%) while minor arterials (12%) and collectors (3%) had a lesser role. Finally, the total recorded mileages via each functional roadway classification was multiplied by estimated uncompensated marginal costs per loaded truck-mile for interstate ($0.059), principal arterial ($0.259), minor arterial ($0.359), and collector ($0.876) roadways to arrive at a range of total annual pavement cost estimates. Similarly, the spatial model solution featuring introduction of the hypothetical intermodal terminal in Lubbock was analyzed and estimated parameters representing various functional roadway classifications used to estimate an annual pavement cost.

When the current private operator in Lubbock is assumed to handle 500,000 bales, the analysis shows 9.80 million loaded truck-miles would be expended in assembling west Texas cotton to the existing cotton marketing facilities in Lubbock and Dallas-Fort Worth, and when the existing Lubbock operation handles 750,000 bales, total loaded truck-miles decline to 9.02 million. As expected, total loaded truck-miles decline when the current Lubbock operator handles greater volumes since less west Texas cotton is routed to the distant Dallas-Ft. Worth intermodal terminals. The corresponding uncompensated annual pavement cost associated with shipment of 500,000 bales via Lubbock is an estimated $2.26 million, and with 750,000 bales, an estimated $2.08 million.

The cotton marketing system featuring the hypothetical intermodal terminal in Lubbock and existing intermodal terminals in Dallas-Fort Worth is estimated to annually expend 5.27 million loaded truck-miles and incur annual uncompensated pavement costs of $1.11 million. Based on these values, introduction of the hypothetical intermodal terminal in Lubbock is estimated to reduce uncompensated pavement cost between $0.97 million ($2.08 − $1.11 = $0.97) and $1.15 million per year ($2.26 − $1.11 = $1.15).

Effect of Intermodal Terminal on CO_2 Emissions

To calculate the anticipated reduction in CO_2 emissions associated with introduction of the hypothetical intermodal terminal in Lubbock, an approach similar to that used in estimation of roadway pavement costs was followed. The CO_2 emissions associated with the current private intermodal terminal operation in Lubbock when handling 500,000 bales and then 750,000 bales were estimated with the spatial model. Then, the resulting range of CO_2 emission values were contrasted with the CO_2 emission estimate associated with introduction of the hypothetical intermodal terminal in Lubbock.

The developed spatial model records the selected truck assembly system for each origin-destination combination and *ex post* the spatial model solution aggregates the mileage for each assembly system on selected corridors. The resulting mileage values for each truck assembly system in combination with estimates regarding backhaul and empty-mile ratios on evaluated corridors

were used in combination with estimates of CO_2 emissions per loaded (2,003.7 grams) and empty mile (1615.8 grams) to convert mileages into CO_2 emissions.

Total annual CO_2 emissions attributable to truck assembly were estimated to be 38,667 short tons when marketing west Texas cotton if the private terminal operator in Lubbock handles 500,000 bales and truck-assembled cotton to Dallas-Fort Worth terminals is included in the CO_2 computation. Total annual CO_2 emissions attributable to truck assembly are estimated to be 35,566 short tons when the current Lubbock operator expands volume to 750,000 bales. As expected, estimated CO_2 emissions decline when the current Lubbock operator handles greater volumes since less west Texas cotton is required to travel extended distances into Dallas-Ft. Worth intermodal terminals.

If the intermodal terminal in Lubbock were implemented (two million bales), total CO_2 emissions would decline to 20,588 short tons; this yields reductions in CO_2 emissions that range from 14,978 (35,566 − 20,588 = 14,978 short tons) to 18,079 (38,667 − 20,588 = 18,079 short tons) short tons per year. Based on the Tol (2005) estimate regarding the marginal cost of CO_2 ($39 per short ton), the estimated annual value of reduced CO_2 emissions range between $0.584 million (14,978 short tons x $39= $584,142) and $0.705 million (18,079 short tons x $39 = $705,081) per year.

CONCLUSIONS

This study examines the economic feasibility of investment in an intermodal terminal in west Texas to accommodate cotton exports and explores its implications for reducing roadway maintenance costs and CO_2 emissions. Cotton is a leading agricultural commodity in Texas, which is highly dependent on the international market and truck transport from west Texas to the Dallas-Fort Worth metroplex for purposes of accessing containerized railroad transportation to West Coast ports. Much of the analysis was accomplished with a spatial model representing the U.S. cotton industry. The least-cost model features cotton handling, storage, and five transportation systems that link cotton gins to warehouses and ultimately to intermodal terminals, domestic textile mills, U.S. port areas, and border-crossing sites.

The analyses show an intermodal terminal in west Texas' intensive cotton-production region (Lubbock) to be economically viable. It is estimated that the facility could attract about two million bales, or nearly 30% of Texas' average cotton production. The largest intermodal terminal examined in this study (18,000 container shipments per year or 1.58 million bales) would require an investment of $10.69 million and would be expected to earn a rate of return on investment exceeding 20%. Additional analyses show the 18,000 container-per-year terminal would attract profitable volumes during the region's lowest cotton-production years, but would be vulnerable if an existing intermodal terminal at a nearby location (Amarillo) were to commence cotton shipments to West Coast ports.

Implementation of an intermodal terminal in west Texas that handles approximately two million cotton bales is estimated to reduce truck (80,000-pound, five-axle) travel on state roadways by an estimated 3.75 to 4.53 million loaded truck-miles and to lower annual pavement expenditures by approximately $1 million. The reduced truck-miles expended to assemble Texas cotton to intermodal facilities are estimated to reduce CO_2 emissions by 42% (14,978 short tons) to 47% (18,079 tons) relative to the current marketing system. The estimated value of the reduced CO_2 emissions range between $0.584 and $0.705 million per year.

In summary, the analysis indicates investment in intermodal terminals in rural areas may offer opportunities to improve commodity marketing efficiency, and reduce roadway maintenance costs and vehicle emissions.

References

Andrieu, N. and L. Weiss. *Transport Mode and Network Architecture: Carbon Footprint as a New Decision Metric.* Master's thesis. Massachusetts Institute of Technology, 2008. Accessed September 12, 2010. http://dspace.mit.edu/handle/1721.1/45250.

Babcock, M. W., J. L. Bunch, J. Sanderson, and J. Witt. *Economic Impacts of Railroad Abandonment on Rural Kansas Communities.* Kansas Department of Transportation, Report No. KS-03-4, 2003a, Topeka, Kansas.

Babcock, M.W., J. L. Bunch, J. Sanderson, and J. Witt. "Impact of Short Line Railroad Abandonment on Highway Damage Costs: A Kansas Case Study." *Journal of the Transportation Research Forum* 57 (4),(2003b): 105–121.

Berwick, M. *Feasibility of a Logistics Center Including Container/Trailer Intermodal Transportation in Fargo/Moorhead.* Report DP193, Upper Great Plains Transportation Institute, North Dakota State University, Fargo, North Dakota, September 2007. Accessed June 18, 2010. http://www.ugpti.org/pubs/pdf/DP193.pdf.

Bitzan, J. and D. Tolliver. *North Dakota Strategic Freight Analysis. Item IV. Heavier Loading Rail Cars.* MPC Report 01-127.4, Mountain-Plains Consortium: A program of Upper Great Plains Transportation Institute, North Dakota State University, Fargo, North Dakota, 2001.

Cotton Board. *Gin Code List*, 2009. Accessed May 18, 2010. http://www.cottonboard.org/CB_Home.aspx?SectionID=4&ContentURL=CBBuyer1\gincodelist.htm&TabID=2&ContentType=2&ContentURLID=29.

Environmental Protection Agency (EPA). *MOVES Motor Vehicle Emissions Simulator.* Office of Transportation and Air Quality, 2010. Accessed August 12, 2010. http://www.epa.gov/otaq/models/moves/index.htm.

Fellin, L., S. Fuller, J. Kruse, S. Meyers, and A. Womack. "The Upper Mississippi and Illinois Rivers as Grain Transport Arteries: A Spatial Equilibrium Analysis." *Journal of the Transportation Research Forum* 47 (2), (2008):73–88.

Franzese, O., H. E. Knee, and L. Slezak. *Effect of Tires on Class-8 Heavy Truck Fuel Efficiency,* 2009. Accessed March 23, 2010. http://info.ornl.gov/sites/publications/files/ Pub20686.pdf.

Fuller, S., J. Robinson, F. Fraire, and S. Vadali. *Improving Intermodal Connectivity in Rural Areas to Enhance Transportation Efficiency: A Case Study.* University Transportation Center for Mobility, Texas Transportation Institute, The Texas A&M University System, May 2011. Accessed June 3, 2011. http://utcm.tamu.edu/publications /final_reports/Fuller_07-07.pdf

Fuller, S., J. Park, and J.R.C. Robinson. "Cotton Transportation and Logistics: A Dynamic System." Transportation Research Forum, *48th Proceedings of the Transportation Research Forum*, Boston, Massachusetts, March 2007. Accessed March 20, 2008. http://www.trforum.org/forum/viewabstract.php?id=233

Intercontinental Exchange (ICE). *Cotton Certified Stock Report,* 2009. Accessed May 8, 2010. https://www.theice.com/marketdata/reports/ReportCenter.shtml?reportId=4 &productId=588&hubId=732.

Lubbock Economic Development Alliance. *Property Values,* 2008. Accessed March 15, 2010. http://www.lubbockeda.org/.

Manta. *Broadwoven Fabric Mills, Companies in the U.S.,* 2009a. Accessed May 16, 2010. http://www.manta.com/mb_34_E90D3_000/broadwoven_fabric_mills_cotton.

Manta. *Cotton Spinning Mills in the U.S*., 2009b. Accessed May 16, 2010. http://www.manta.com/mb_34_E9119_000/yarn_spinning_mills.

McKinnon, A. *CO_2 Emissions from Freight Transport in the UK*. Report prepared for the Climate Change Working Group of the Commission for Integrated Transport, Logistics Research Center, Heriot-Watt University, Edinburgh, Scotland, 2007. Accessed July 21, 2010. http://resilientcities.gaiaspace.org/mushin/files/-1/7/2007climatechange-freight.pdf.

Michigan Department of Transportation and the U.S. Department of Transportation. *Detroit Intermodal Freight Terminal: Wayne and Oakland Counties, Cost Estimates*, August 2008.

Minnesota Department of Agriculture and Wilbur Smith Associates. *Assessing Feasibility of Intermodal Transport of Agricultural and Related Products on Short Line and Regional Railroads.* Minnesota Department of Agriculture, 2008. Accessed June 8, 2010. http://www.mda.state.mn.us/news/publications/food/business&marketing/ intermodaltrans.pdf.

Stewart, R., L. Ogard, and F. Harder. "Intermodal Terminal Requirements for Small to Medium Size Communities: A Case Study." Transportation Research Board, 83rd Annual Meeting, Washington, D.C., January 2004.

Surface Transportation Board (STB). *Public Use Waybill*, 2009. Accessed May 24, 2010. http://www.stb.dot.gov/stb/industry/econ_waybill.html.

Texas Cotton Association. *Texas Warehouse Tariffs,* 2009.Accessed April 22, 2010. http://www.storesonline.com/site/417921/page/428041.

Tol, R.S. "The Marginal Damage Costs of Carbon Dioxide Emissions: An Assessment of Uncertainties." *Energy Policy* 33 (16), (2005): 2064–2074.

Tolliver, D. and HDR Engineering, Inc. *Benefits of Rail Freight Transportation in Washington: A Multimodal Analysis*. Appendix D. Washington State Department of Transportation, Olympia, Washington, 2000.

U.S. Census Bureau. *Current Industrial Reports. M313P-Consumption on Cotton System and Stocks, Table 2. Consumption and Stocks, End of Period, Held by Consuming Establishments of Cotton, Manmade Fiber Staple, and Linters,* 2009a. Accessed May 14, 2010. http://www.census.gov/manufacturing/cir/historical_data/m313p/index.html.

U.S. Census Bureau. *Current Industrial Reports. M313P-Consumption on Cotton System and Stocks, Table 2A. Stocks, End of Period, of Cotton Held in Public Storage and at Compresses,* 2009b. Accessed May 14, 2010. http://www.census.gov/manufacturing/ cir/historical_data/m313p/index.html.

U.S. Department of Agriculture (USDA). *Cotton and Wool Yearbook 2009*. Economic Research Service, 2009a. Accessed May 10, 2010. http://usda.mannlib.cornell.edu/ MannUsda/viewStaticPage.do?url=http://usda.mannlib.cornell.edu/usda/ers/89004/./2009/index.html

U.S. Department of Agriculture (USDA). *Cotton On-line Processing System*. Farm Service Agency, 2009b. Accessed June 12, 2010. https://dlnt01.fsa.usda.gov/logon.jsp.

U.S. Department of Agriculture (USDA). *Cotton Estimates*. Office of the Chief Economist, World Agricultural Demand and Supply Estimates, 2010. Accessed February 12, 2011. http://usda.gov/oce/commodity/wasde

U.S. Department of Agriculture (USDA). *USDA-AMS Cotton Program, National Database*. Agricultural Marketing Service, 2009c. Accessed May 22, 2010. http://www.ams.usda.gov/AMSv1.0/getfile?dDocName=STELDEV3018864.

U.S. Department of Agriculture (USDA). *Quick Stats 1.0*. National Agricultural Statistical Service, 2009d. Accessed May 23, 2010. http://www.nass.usda.gov/.

U.S. Department of Energy (USDOE). *Monthly On-Highway Retail Diesel Prices.* U.S. Energy Information Administration, 2009. Accessed May 18, 2010. http://tonto.eia.doe.gov/oog/info/wohdp/diesel.asp.

U.S. Department of Transportation (USDOT). *Federal Highway Cost Allocation Study: Summary Report.* Federal Highway Administration, 1997. Accessed May 22, 2010. http://www.fhwa.dot.gov/policy/hcas/summary/index.htm.

U.S. Department of Transportation (USDOT). *FHWA Functional Classification Guidelines.* Federal Highway Administration, 2000a. Accessed August 10, 2010. http://www.fhwa.dot.gov/planning/fctoc.htm.

U.S. Department of Transportation (USDOT). *Price Trends for Federal-Aid Highway Construction.* Federal Highway Administration, 2006. Accessed February 23, 2011. http://www.fhwa.dot.gov/programadmin/pt2006q1.cfm.

U.S. Department of Transportation (USDOT). Federal Highway Administration, *Comparative Evaluation of Rail and Truck Fuel Efficiency on Competitive Corridors*, 2009. Accessed February 3, 2011. http://www.fra.dot.gov/Downloads /Comparative_ Evaluation_Rail_Truck_Fuel_Efficiency.pdf.

U.S. Department of Transportation (USDOT). Federal Highway Administration, *Construction Cost Trends for Highways, Table PT-1,* 2010. Accessed August 10, 2010. http://www.fhwa.dot.gov/ohim/nhcci/pt1.cfm.

Upper Great Plains Transportation Institute. *Feasibility of a Logistics Center Including Container/Trailer Intermodal Transportation in the Fargo/Moorhead Area.* North Dakota State University, September 2007.

Vachal, K. and M. Berwick. *Exporting Local Grains via Container from an Illinois River Agricultural Hub,* 2008. Accessed June 14, 2010. http://www.ilsoy.org/_data/media Center/files/608.pdf.

Victoria Transport Policy Institute. *Parking and Loading Space Minimum Requirements, Table 5.1-6(f*), 2008. Accessed April 13, 2010. http://www.cityofvernon.org/assets/docs /ParkRegs.pdf.

Warner, J. and M. S. Terra. "Assessment of Texas Short Line Railroads." Transportation Research Board, 85th Annual Meeting, Washington, D.C., 2006. Accessed March 12, 2010. http://ctr.ra.utk.edu/LRRFT/cmte_activities/papers/ TRBAM%2006-Warner Terra.pdf.

Washington State Department of Transportation. *East Washington Grain-Hauling Short-Line Rails.* Study performed by HDR Engineering, Inc., and Denver Tolliver, February 2003. Accessed March 24, 2009. http://www.palouse.org/rtpo/PRTPappendix Cgrainhaultin_rpt.pdf.

Wilson, W., B. L. Dahl, R. Taylor, and W. Koo. *Grain Shipments on the Mississippi River System: A Long-Term Projection*. Center for Agricultural Policy and Trade Studies, Department of Agricultural Economics, North Dakota State University, July 2007. Accessed May 22, 2009. http://ageconsearch.umn.edu/bitstream/9080/1/aer605.pdf.

WISERtrade. *Foreign Trade Data*, 2009. Accessed March 18, 2010. http://www.wisertrade.org/home/index.jsp.

Stephen Fuller *is regents professor emeritus in the department of agricultural economics at Texas A&M University in College Station, Texas. Fuller's research focuses on agricultural transportation and marketing issues.*

John Robinson *is a professor and extension economist-cotton marketing in the department of agricultural economics at Texas A&M University in College Station, Texas. His professional emphasis is in cotton economics and cotton transportation and logistics issues.*

Francisco Fraire *was formerly a research assistant in the department of agricultural economics at Texas A&M in College Station, Texas, where he received a Ph.D. in agricultural economics in 2011. Fraire is currently a senior associate at MSCI, where he is employed as a risk management specialist. He is currently located in MSCI's Monterrey, Mexico, office.*

Sharada Vadali *is associate research scientist in the Texas Transportation Institute at Texas A&M University in College Station, Texas.Vadail's research focus is in mobility analysis.*

Border Zone Mass Transit Demand in Brownsville and Laredo

by Thomas M. Fullerton, Jr., and Adam G. Walke

This study examines whether economic conditions in Mexico influence public transportation ridership levels in the border cities of Brownsville and Laredo, Texas. Besides the standard variables generally utilized to model bus ridership, additional indicators included in the empirical analysis are northbound pedestrian traffic and the real exchange rate index. Seemingly unrelated regression parameter estimates suggest that the volume of pedestrian border crossings in both cities is positively related to changes in ridership. The real exchange rate index in Laredo is negatively related to fluctuations in ridership, implying that peso appreciation increases transit utilization in this border city.

INTRODUCTION

Advocates of public transportation argue that it can play an important role in reducing air pollution and traffic congestion. Such outcomes can occur if it can reduce personal automobile usage. There is speculation that higher gasoline prices might convince people to ride public transit rather than drive. For instance, a local newspaper in south Texas recently attributed an observed increase in McAllen bus ridership to higher fuel prices (Janes 2011). Similarly, a higher level of transit service or lower fares may persuade more people to use public transportation. Econometric analysis may help provide accurate information about the extent to which these and other factors influence ridership.

Aside from the potential benefits from reduced automobile traffic, public transit is also promoted as a means of increasing mobility when using private automobiles is not a viable alternative. Much of the attention in this regard has centered on the role of transit in linking unemployed people with employment opportunities in urban areas (Blackley 1990, Hughes 1991). Less understood is the role of public transportation in linking pedestrian border crossers with destinations such as shopping centers in cities located at international boundaries. In some border zones, public transportation has been proposed as a way of facilitating cross-border shopping (Dascher and Haupt 2011). Such projects could produce economic benefits in areas such as the southern border of Texas, where Mexican shoppers constitute a significant portion of retail trade (Coronado and Phillips 2007). This study examines a variety of factors that may affect transit demand, including the impact of cross-border traffic and international economic factors on bus ridership.

The sample includes data from two U.S. border cities: Brownsville and Laredo, Texas. Several factors make these cities good candidates for a study of cross-border impacts on transit ridership. First, as of 2009, they jointly receive more than 6.6 million pedestrian crossings per year. That is 35% of total pedestrian crossings into Texas and 16% of all pedestrian crossings into the United States (BTS 2011). Second, the central municipal bus terminal in each city is within walking distance of the U.S.–Mexico border, making transit accessible to pedestrians crossing the border. Third, both cities have well-established public transportation systems dating back to at least 1978, making time series analysis feasible. There is a long-standing assumption that pedestrian border crossers form a substantial portion of transit ridership in these cities (TDHPT 1979). One purpose of the present effort is to determine whether, and to what extent, such claims can be quantified.

The demand for public transportation is affected by fares, the level of service, urban population, income, car ownership, and the price of substitutes such as automobile travel. These determinants of ridership, along with the impact of cross-border traffic, provide the basic inputs to the analysis of transit demand presented here. This section is followed by a review of relevant literature and a description of the methodology utilized. Empirical results are presented next, followed by a conclusion.

LITERATURE REVIEW

Much of the literature on determinants of the demand for public transportation concerns variables that are controlled by transit system administrators, such as the level of transit service or fares. Several studies show that changes in these variables can have a substantial impact on transit ridership (Kain and Liu 1999, Taylor et al. 2009). The demand for public transportation is, in most cases, inelastic with respect to fares (Pham and Linsalata 1991, Paulley et al. 2006), although fare elasticities may vary substantially across regions (Dargay and Hanly 2002). Some studies suggest that transit demand is also inelastic with respect to the level of service (Paulley et al. 2006), although other evidence points to an elastic relationship (Holmgren 2007).

The level of service is often measured by a variable such as vehicle revenue hours, which is correlated with the density of bus routes and the frequency of departures. Service, however, is inversely related to the time costs of using public transportation, i.e., the costs of time spent walking to boarding stations, waiting for transportation to arrive, and travelling to a given destination (Frankena 1978). The level of service is sometimes also construed as a measure of the supply of public transportation. Peng et al. (1997) address the issue of simultaneity between service and ridership by estimating separate transit supply and demand equations.

Other determinants of transit ridership are beyond the control of administrators. For example, the level of transit patronage is highly correlated with urban area population (Taylor et al. 2009). Income is also likely to influence the level of ridership, and while some evidence suggests that public transportation is an inferior good (Nizlek and Duckstein 1974), others imply that it is a normal good (Chiang et al. 2011). Bresson et al. (2004) argue that ridership is positively correlated with income but negatively correlated with car ownership. Since income and car ownership are also correlated, omitting a measure of car ownership from a ridership equation tends to introduce downward bias on the income elasticity estimate.

Another variable included in many transit demand equations is a measure of the price of substitutes for public transportation. Motor vehicles are the main substitute for transit. Frankena (1978) finds that, of the various costs associated with owning a vehicle, only gasoline price has a statistically significant impact on transit ridership. In a study of seven U.S. cities, Wang and Skinner (1984) find that the elasticity of ridership with respect to gasoline prices ranges from 0.08 to 0.80. More recently, Lane (2010) confirms that gasoline price fluctuations can significantly impact the demand for public transportation.

There is little literature that directly addresses the impact on public transportation of proximity to an international border. Dascher and Haupt (2011) briefly discuss some attempts to extend public transit across the German-Polish border to facilitate cross-border shopping, among other things. While cross-border shopping is mutually beneficial for both the shoppers and the businesses they frequent, other groups may disapprove of public infrastructure projects aimed at facilitating trans-boundary commerce. The model explains the relative strength of these opposing interests based on factors such as inter-regional mobility, centralization of decision making, and patterns of property ownership. The model does not, however, attempt to determine the extent and nature of demand for cross-border public transportation.

While there is only limited academic work directly relating border region dynamics to patterns of transit ridership, there is a rich literature concerning trans-boundary traffic flows, especially along

the U.S.–Mexico border. Much of it centers on pedestrian border crossings, and pedestrians are probably the group of entrants most likely to access public transportation in border cities. Survey evidence presented by Charney and Pavlakovich-Kochi (2002) indicates that 83% of pedestrians returning from trips to Arizona state that their primary purpose was shopping as compared with 68% of motor vehicle passengers. Similarly, Ghaddar and Brown (2005) find that 85% of cross-border visitors to Texas come for the purpose of shopping. Based on a survey conducted at the U.S.-Mexico border south of San Diego, Herzog (1991) finds that pedestrians comprise at least 50% of the Mexican nationals who cross the border to shop for food, clothing, or articles for the home. None of these surveys explicitly asks pedestrians whether or not they use transit on the U.S. side of the border.

Other analysts consider how economic conditions in Mexico influence the volume of pedestrian and vehicle traffic at ports of entry into the U.S. Fullerton (2000) finds that movements in the real peso-dollar exchange rate influence the volume of bridge traffic from Ciudad Juárez into El Paso. De Leon et al. (2009) conducted a similar study, but consider pedestrian traffic across the international bridges separately from motor vehicle traffic. Pedestrian crossings are positively related to Mexico's industrial production index and negatively related to bridge tolls. There is also a correlation between pedestrian crossings and the real exchange rate, but the direction of this relationship is uncertain. This ambiguity may arise because the data do not distinguish the nationality of border crossers. Thus, it is difficult to disentangle the effects of a shift in the exchange rate, which is likely to be different for Mexican and U.S. nationals.

Giermanski (1997) notes that cross-border shopping makes an important contribution to the economies of Texas border cities. Coronado and Phillips (2007) estimate that actual retail sales in Texas border cities exceed predicted sales by $1.9 billion. The surplus is attributed to Mexican nationals who cross the border into the U.S. to shop. Results of a mail survey conducted by Patrick and Renforth (1996) indicate that, between 1994 and 1995 when the Mexican peso lost more than half of its value relative to the dollar, retail sales in Texas border cities dropped by 42%. This supports the argument that cross-border shopping is an important feature of the border economy, at least in Texas.

While the literature on traffic across the U.S.-Mexico border does not specifically address public transportation, it provides insight into the motivations and economic impact of pedestrians who cross the border. One objective of this study is to quantify the link between pedestrian traffic through international ports of entry and public transportation networks along the Texas-Mexico border. Because Texas has several large border cities with well-developed public transportation systems, and receives 45% of all pedestrian entrants into the United States, the Texas-Mexico border region is well suited to a study of trans-boundary impacts on transit ridership (BTS 2011). In order to take advantage of potential border region covariances, the analysis is conducted using a seemingly unrelated regression estimator (Zellner 1962). Tests are also carried out for potential endogeneity among the variables utilized.

METHODOLOGY

Data

Laredo's public transportation system, El Metro, traces its origin to 1976. Its counterpart in Brownsville, the Brownsville Urban System, owes its existence to the city's acquisition of two privately-owned bus lines in 1978 (TDHPT 1979). Public transit in both cities is concentrated in fixed-route bus transportation, but demand response services are also provided (NTD 2011). The data on fare, service, and ridership in these cities are collected from Texas Transit Statistics (TTS), a report issued annually by the Texas Department of Transportation (TDT 1983-2009). Ridership, the

dependent variable, is measured by the number of unlinked passenger trips per year and the level of service is measured by vehicle hours per year.

The calculation of fare is somewhat more complicated. While transit agencies often offer travel passes or fare discounts to particular groups of riders, the agencies that form the basis of this study do not provide historical information on each fare category. Therefore, the average fare is calculated by dividing annual farebox revenue by the number of passenger trips each year. The TTS figures for Laredo vehicle hours, fare revenue, and ridership in 2005 are exceptionally low; between 48% and 54% lower than the 2004 figures. Yet, data from the Laredo City Budget Department show that El Metro's operating expenditures and fare revenue steadily increased during that period. To resolve this contradiction, the service, fare and ridership data for 2005 are taken from the National Transit Database (NTD 2011), which provides figures similar to those of TTS in the other years for which the two datasets overlap.

Average fare data are adjusted for inflation using the Consumer Price Index (CPI, 1982-1984 = 100) from the website of the Federal Reserve Bank of St. Louis (FRB 2011). The real price of unleaded regular gasoline is obtained from the website of the Energy Information Administration (EIA 2011). Data on unemployment are from the website of the Bureau of Labor Statistics (BLS 2011) for years since 1990 and from the Texas Labor Market Review for prior years (TEC 1983-89). Population data are retrieved from the website of the Bureau of Economic Analysis (BEA 2011). The real peso-dollar exchange rate index is obtained from the Border Region Modeling Project at the University of Texas at El Paso (UTEP 2011). The number of pedestrian border crossings is provided to the authors by U.S. Customs and Border Protection.

The number of vehicle registrations is taken from the website of the Texas Department of Transportation (TDT 2011) from 1996-2007 and from the District and County Statistical Data reports (TDT 1987-95) and the Texas Almanac (Dallas Morning News 1984-86, 2008-09). The vehicle registration data are not available for Brownsville or Laredo for 1983 and 1994. Vehicle registration data are, however, available for El Paso, Texas, for both years through the Border Region Modeling Project (UTEP 2011) and the El Paso vehicle registration data are highly correlated with those for Brownsville and Laredo. The number of registered vehicles in El Paso and a time trend are used as regressor variables to allow estimating missing observations (Friedman 1962, Fernandez 1981).

Prior research indicates that unobserved social and economic factors may collectively exert long-term upward or downward pressure on transit patronage. The impact of such factors can be incorporated into a regression equation by means of a deterministic time trend (Wang and Skinner 1984, de Rus 1990, Romilly 2001, Lane 2010, Gkritza et al. 2011). Time is therefore included as an exogenous variable to capture any secular trend in ridership that is not explained by the other independent variables. A trend variable is not only of interest in its own right, but is useful in controlling for the effect of time on other explanatory variables in the equation. A regression equation that includes a trend variable yields the same parameter estimates that would be obtained from a regression in which all the variables are de-trended (Lovell 2008). De-trending is useful when the effect on ridership of short-term variations in an explanatory variable is obscured by the trend component of that variable. Excluding a time trend is sometimes found to substantially affect parameter estimates in transit demand equations (Dargay and Hanly 2002, Lane 2010).

Time series data, such as those analyzed here, are often non-stationary. Augmented Dickey-Fuller tests indicate that several of the variables are stationary in level form, while others are non-stationary. Faced with a similar situation, in which both stationary and non-stationary variables form part of a regression equation, Gkritza et al. (2011) utilize a linear time trend in conjunction with annual indicator variables to avoid spurious estimation results. As noted above, a time trend is also utilized in the present study.

Summary statistics are presented for all of the variables except for the time trend in Table 1 and 2. The sample period begins in 1983 and ends in 2009. The average ridership level in Laredo over the sample period is about 4.1 million trips per year compared with an average of 1.7 million trips

Table 1: Brownsville Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	No.
Passenger Trips	1,657,263	126,191	1,333,719	1,909,292	27
Real Fare (cents)	34.938	3.955	29.016	48.495	27
Vehicle Hours	67,728	11,954	46,434	83,714	27
Real Gasoline Price (cents)	175.185	45.032	124	301	27
Unemployment	13,338	2,467	8,548	16,566	27
Registered Vehicles (000's)	178.233	42.097	118.561	261.453	27
MSA Population	310,827	51,285	238,878	396,371	27
Border Crossings (000's)	3,436.222	599.435	2,546.720	5,036.891	27
Real Exchange Rate Index	100.969	15.735	78.764	145.238	27

Table 2: Laredo Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	No.
Passenger Trips	4,059,538	512,666	3,155,122	5,012,758	27
Real Fare (cents)	31.086	3.851	21.423	37.479	27
Vehicle Hours	135,843	39,465	88,830	186,304	27
Real Gasoline Price (cents)	175.185	45.032	124	301	27
Unemployment	6,604	1,635	4,251	11,010	27
Registered Vehicles (000's)	96.946	30.713	54.515	159.624	27
MSA Population	172,567	41,662	115,419	241,438	27
Border Crossings (000's)	4,405.490	759.044	3,112.505	6,674.293	27
Real Exchange Rate Index	100.969	15.735	78.764	145.238	27

in Brownsville. Laredo annually registers 4.4 million pedestrian border crossings on average, while 3.4 million visitors walked through the ports of entry into Brownsville each year. Thus, the ratio of pedestrian border crossings to transit passenger trips is roughly 2:1 in Brownsville but closer to 1:1 in Laredo.

Figures 1 through 4 depict the movement of the ridership series for Brownsville and Laredo in comparison to the movement of the real exchange rate index and pedestrian border crossing series. The data for Brownsville do not provide clear evidence of a positive correlation between ridership and pedestrian border crossings (Figure 1) but they do seem to indicate a negative relationship between ridership and the real exchange rate index (Figure 2). In Laredo, on the other hand, there appears to be some positive correlation between ridership and pedestrian border crossings for most of the period (Figure 3) but it is more difficult to discern a negative relationship between ridership and the real exchange rate index (Figure 4).

Figure 1: Brownsville Ridership and Pedestrian BorderCrossings

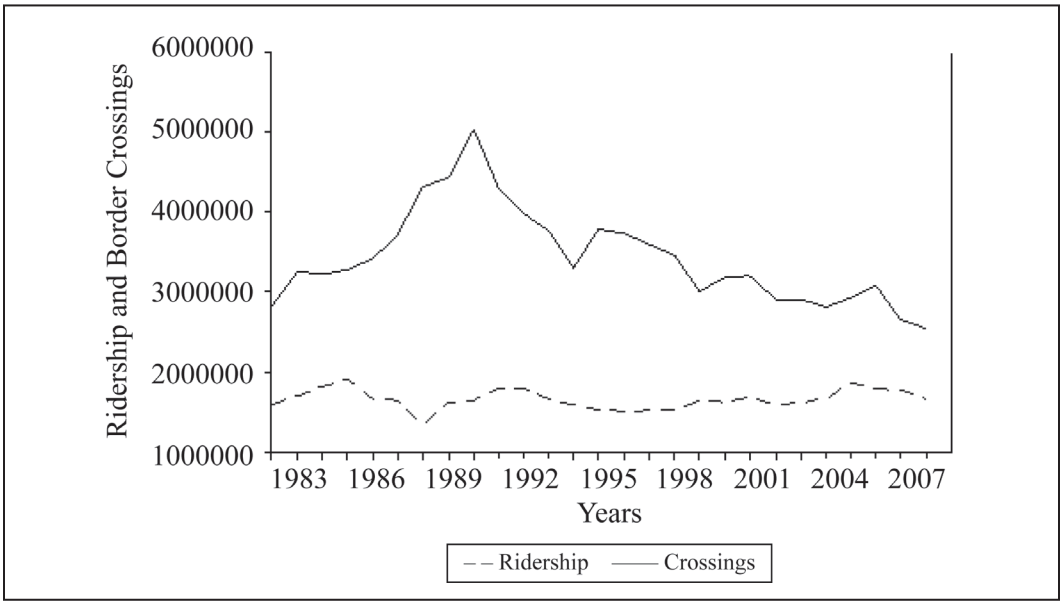


Figure 2: Brownsville Ridership and the Real Exchange Rate Index

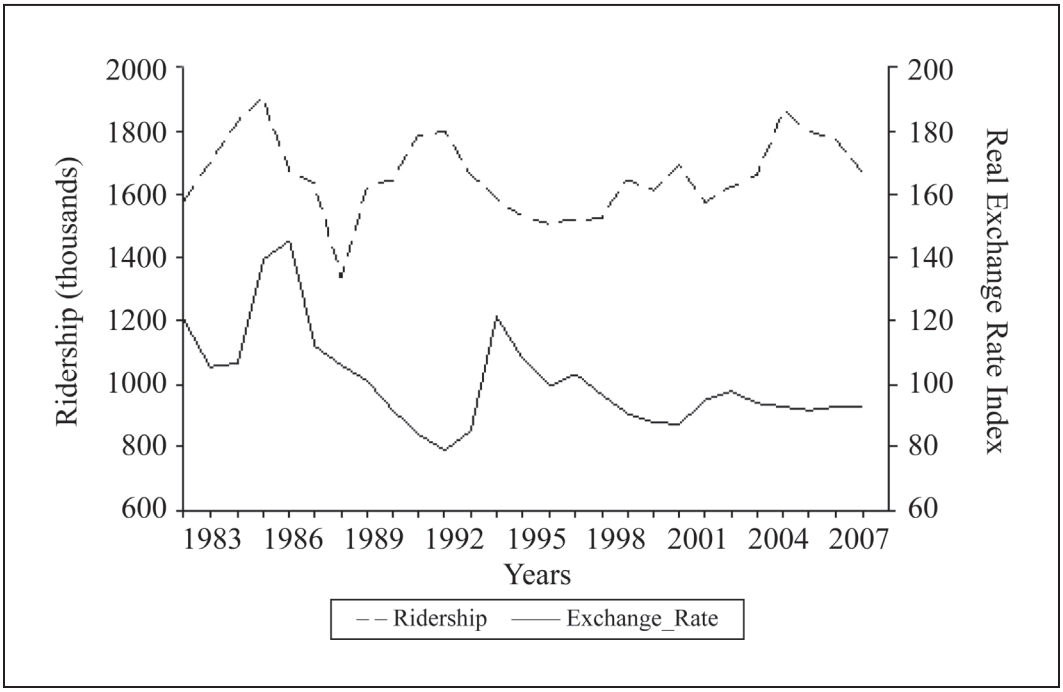


Figure 3: Laredo Ridership and Pedestrian Border Crossings

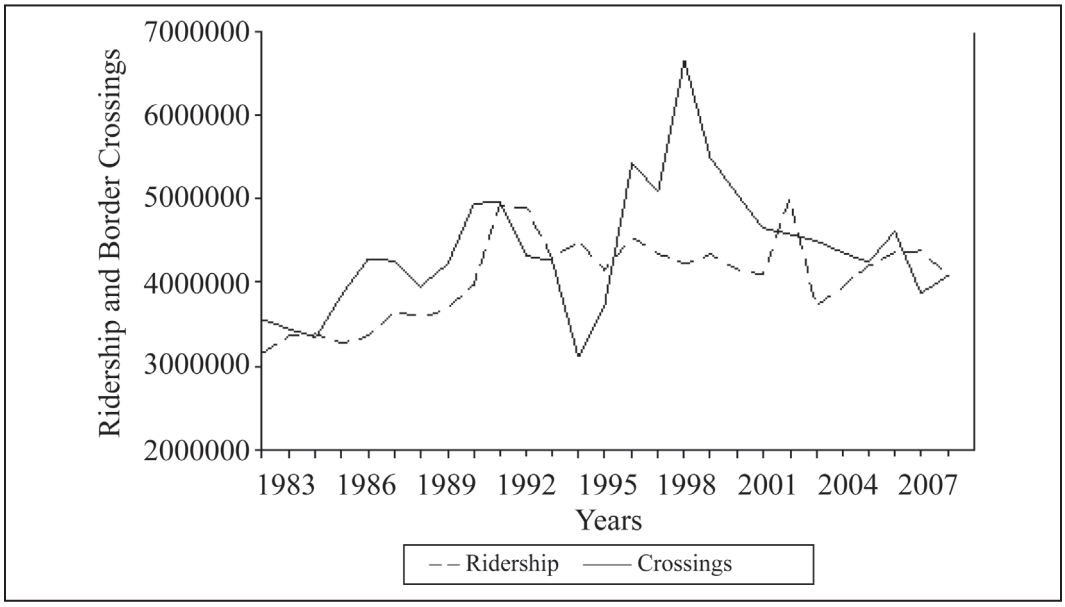
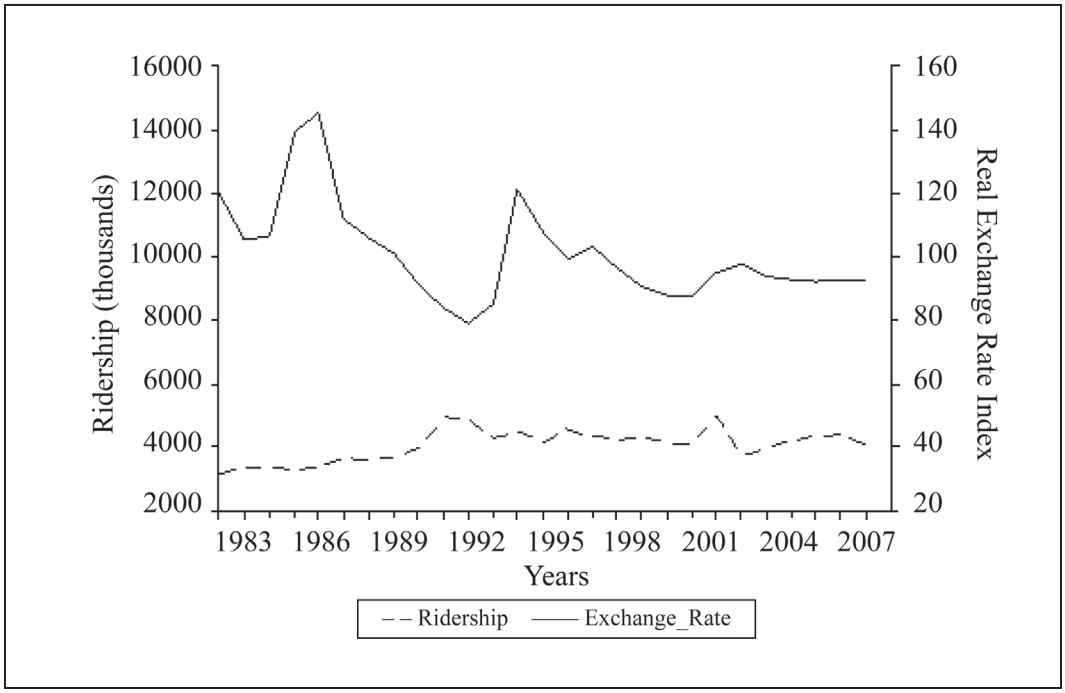


Figure 4: Laredo Ridership and the Real Exchange Rate Index



Analytical Approach

Although the magnitudes of the parameter estimates are likely to vary between Brownsville and Laredo, there is no á priori reason to believe that the signs of these coefficients will also vary. Thus, the following discussion applies equally to both cities. The basic model employed in the analysis of ridership can be expressed in implicit form as follows:

(1) $R_t = F(F_t, S_t, GP_t, U_t, V_t, P_t, T_t, PC_t, XR_t)$

where R_t represents transit ridership, F_t is the average fare, S_t is the level of service (vehicle hours), GP_t is the price of gasoline, U_t is the unemployment rate, V_t is vehicle registrations, P_t is population, T_t is a time trend, PC_t is pedestrian border crossings, and XR_t is the real exchange rate index. No hypothesis is advanced in the discussion that follows regarding the marginal effect of the time trend on ridership. That is because there is not enough information available to predict how multiple unobserved factors may collectively impact long term trends in ridership. The other independent variables are hypothesized to have the following marginal effects on ridership:

(2) $\frac{\partial R}{\partial F} < 0, \frac{\partial R}{\partial S} > 0, \frac{\partial R}{\partial GP} > 0, \frac{\partial R}{\partial U} > 0, \frac{\partial R}{\partial V} < 0, \frac{\partial R}{\partial P} > 0, \frac{\partial R}{\partial PC} > 0, \frac{\partial R}{\partial XR} < 0$

Fares are expected to be negatively related to ridership. An increase in the level of service, measured by vehicle hours, is anticipated to stimulate utilization of transit. Because travel by automobile is a substitute for travel by bus, higher gasoline prices are also expected to increase transit patronage. A higher level of unemployment, which is usually associated with lower income levels, is predicted to increase ridership. Car ownership, represented by vehicle registrations, is predicted to vary inversely with transit patronage. Holding other factors constant, a larger population is anticipated to expand transit usage. Pedestrian border crossings are hypothesized to be positively related to ridership. Finally, an increase in the value of the Mexican peso relative to the U.S. dollar is hypothesized to increase cross-border shopping and transit usage by Mexican nationals. An increase in the value of the peso relative to the dollar is reflected in a decrease of the real exchange rate index because the latter is defined as pesos per dollar in inflation-adjusted terms. Therefore, a negative relation is expected to exist between the real exchange rate index and ridership.

Because the number of vehicle hours per year can be construed as a measure of the supply of public transportation, the presence of this variable in a public transportation demand equation raises the prospect of simultaneity. Average fare may also be endogenous because it is calculated as the ratio of total fare revenue to total ridership. Changes in this ratio may reflect changing patterns of ridership rather than the actual changes in ticket prices (de Rus 1990). Alternatively, the average ticket price may depend, to some extent, on the total volume of ridership. To determine whether simultaneity exists in either average fares or vehicle hours, artificial regression tests are conducted for the Brownsville and Laredo ridership equations (Davidson and MacKinnon 1989).

Next, separate regression equations are estimated for both cities by the method of ordinary least squares. If there is evidence that the disturbance terms in the regression equations for each city are correlated, more efficient coefficient estimates may be obtained using the seemingly unrelated regression parameter estimation method. Zellner (1962) shows how knowledge of the covariance between error terms in separate equations can be incorporated into parameter estimates through a generalized least squares (GLS) procedure. For a system of seemingly unrelated equations, the GLS estimator in matrix form is as follows:

(3) $\hat{\beta}_{GLS} = (X' H' HX)^{-1} X' H' Hy = (X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} y$

If the covariance between the disturbances of equations i and j in identical time periods (the contemporaneous error covariance) is represented by σ_{ij}, then Σ is equivalent to the following when there are only two equations:

$$(4)\quad \Sigma = \begin{bmatrix} \sigma_{11} I & \sigma_{12} I \\ \sigma_{21} I & \sigma_{22} I \end{bmatrix}$$

In practice, the error variances and cross-equation covariances are unknown and must, therefore, be estimated. If the error terms exhibit substantial contemporaneous covariance across equations, the seemingly unrelated regression procedure will be used.

The seemingly unrelated regression model as presented does not allow for serially correlated error terms (Zellner 1962). To correct for first to 12th-order serial correlation, Gkritza et al. (2011) incorporate autoregressive parameters into a seemingly unrelated regressions model. In the current case, where there are only 27 observations and nine explanatory variables for each equation, correcting for higher order serial correlation in this manner would result in an unacceptably small number of degrees of freedom. To determine whether the error terms are autocorrelated, Q-statistics are calculated for the regression residuals and these are compared against critical values of the Chi-square distribution (Pindyck and Rubinfeld 1998).

There are various reasons why ridership in Brownsville and Laredo may be affected by the same unobserved factors. Both cities are located in Texas and their transit systems are thus affected by similar state regulations and funding procedures. They are affected by many of the same climatic conditions. Both cities also share a similar demographic profile that includes a larger share of foreign-born individuals than the average for Texas or the United States (U.S. Census Bureau 2011). Some research shows that recent immigrants are more likely than others to use mass transit (Heisz and Schellenberg 2004). While those factors may be individually insignificant, taken as a whole they may potentially generate substantial error covariance between the Brownsville and Laredo equations.

EMPIRICAL ANALYSIS

To determine whether average fare and vehicle hours are endogenous, they are each regressed on instrumental variables as well as the exogenous variables in the demand equation (Davidson and MacKinnon 1989). For Brownsville, real earnings per employee in the local transportation sector are used as an instrumental variable for vehicle hours. The instruments for fare are the real composite price of fossil fuels and the net public operating cost of transit. Bus driver wages and fuel prices are important costs that transit operators face (Frankena 1978), while net public operating costs reflect governmental allocation of funds to transit operations. Public funding of transit and input prices both influence the level of service provided and the setting of fares but they are not likely to be affected by ridership levels. The residuals from these regressions are statistically insignificant when included as independent variables in the ridership equation. Thus, it is not possible to reject the null hypothesis that both variables are exogenous.

The procedure is repeated for the Laredo variables. The instruments chosen for fare are the number of cooling degree days per year and a one-year lag of cooling degree days. The number of cooling degree days per year affects fares indirectly by influencing costs related to air conditioning, breakdowns, equipment malfunctions and the like. The instrument for vehicle hours is the total number of state and local employees in Laredo. As mentioned above, labor represents an important cost for transit providers, and this cost affects decisions to expand or contract service. Neither temperature patterns nor government employment levels are likely to be correlated with the error term in a transit demand equation. As with the Brownsville variables, the null hypothesis of exogeneity cannot be rejected.

The residual correlation coefficient for the Laredo and Brownsville equations is 0.650. Given substantial error correlation between equations, a seemingly unrelated regression method is used to produce the parameter estimates shown in Tables 3 and 4.The variables are mean-centered and, with the exception of the time trend in the Brownsville equation, all variables are also logarithmically transformed prior to estimation. The coefficients are very similar to the elasticities derived from regressions performed on the variables in level form. The variables included in the regression equation are all statistically significant for at least one of the two cities. Although more parameter estimates are statistically significant in the Brownsville regression output, the coefficient of determination is much higher in that for Laredo. As discussed below, this may be due to multicollinearity among several of the explanatory variables.

The elasticities of demand with respect to fare are estimated to be –0.45 for Brownsville and –0.41 for Laredo. These figures are very similar to the short-run elasticity estimates reported in a national study by Pham and Linsalata (1991) and in an analysis of multiple elasticity studies by Paulley et al. (2006). Both of these estimates suggest that ridership levels in these cities are considerably more responsive to changes in fares than what is implied by the traditional rule-of-thumb elasticity of –0.33 (Cervero 1990).

While the estimates presented here suggest that demand does respond to fare changes, it is also somewhat inelastic with respect to these changes. This implies that fare increases could generate additional revenues that might serve to either increase the level of service or reduce the level of public transit subsidies. However, it is important to remember that the estimates are short-term elasticities. While increasing fares might generate additional revenues in the short term, Paulley et al. (2006) caution that long-term bus fare elasticities may be close to unity. If this is the case, increasing fares may not lead to substantial revenue increases in the long run.

Table 3: Brownsville Ridership

Sample Period: 1983 to 2009

Dependent Variable: Ridership $_t$ (total number of unlinked passenger trips per year)

Variable	Coefficient	Std. Error	t-Statistic	Probability
Fare $_t$	-0.453189	0.114440	-3.960054	0.0004
Vehicle Hours $_t$	0.602066	0.125445	4.799439	0.0000
Gasoline Price $_t$	0.365247	0.078142	4.674150	0.0000
Unemployment $_t$	0.255233	0.078078	3.268956	0.0025
Vehicle Registrations $_t$	-0.603354	0.260029	-2.320335	0.0265
Population $_t$	4.382249	1.266791	3.459330	0.0015
Time Trend $_t$	-0.074575	0.025177	-2.961992	0.0055
Pedestrian Crossings $_t$	0.649275	0.180369	3.599701	0.0010
Exchange Rate $_t$	0.042229	0.102897	0.410399	0.6841
R-Squared	0.566830	Mean Dependent Variable		0
Adjusted R-Squared	0.337505	S.D. Dependent Variable		0.077137
Standard Error of Regression	0.062785	Durbin-Watson Statistic		2.054868
Sum of Squared Residuals	0.067013			

The elasticity of ridership with respect to transit service is estimated to be 0.60 in Brownsville. More surprisingly, the service coefficient for Laredo is negative and insignificant. The negative coefficient persists regardless of whether vehicle miles or vehicle hours are used to measure the level of service. While it seems counterintuitive that an increase in transit service would not result in increased ridership, Small (1997) notes that expanding transit service into suburban areas often does not yield substantial increases in ridership.

Consistent with the hypothesis that travel by bus and travel by automobile are substitutes, a 10% increase in the price of gasoline is found to increase transit usage by 3.7% in Brownsville and 2.0% in Laredo. These results, like those obtained by Wang and Skinner (1984), indicate that a change in gasoline price has a significant positive effect on ridership, but that this relationship is inelastic. If automobiles are substitutes for transit, it is not surprising to find that the number of registered vehicles is negatively correlated with ridership in Brownsville, although the relationship is less statistically significant in Laredo. Brownsville's elasticity of demand with respect to car-ownership is –0.60, which is smaller than the composite elasticity estimate of –1.48 reported by Holmgren (2007).

A 10% increase in unemployment is expected to cause a 2.6% increase in ridership in both Brownsville and a 1.5% increase in Laredo. This positive relationship is consistent with evidence in Nizlek and Duckstein (1974) that ridership moves in tandem with short-term cycles of unemployment. Additional regressions are performed to examine whether changes in personal income affect ridership levels in Brownsville and Laredo. Because income does not appear to explain much of the variation in ridership, it is excluded from the final specification.

Although transit ridership in Brownsville exhibits a secular downward trend, population growth in that city is associated with increased ridership. The population coefficient for Laredo is

Table 4: Laredo Ridership

Sample Period: 1983 to 2009

Dependent Variable: Ridership $_t$ (total number of unlinked passenger trips per year)

Variable	Coefficient	Std. Error	t-Statistic	Probability
Fare $_t$	-0.411995	0.077357	-5.325866	0.0000
Vehicle Hours $_t$	-0.160948	0.202795	-0.793649	0.4329
Gasoline Price $_t$	0.198367	0.109467	1.812118	0.0788
Unemployment $_t$	0.145462	0.070783	2.055032	0.0476
Vehicle Registrations $_t$	-0.364547	0.205281	-1.775849	0.0847
Population $_t$	0.416503	0.489169	0.851451	0.4005
Time Trend $_t$	0.113669	0.064900	1.751448	0.0889
Pedestrian Crossings $_t$	0.164885	0.070609	2.335175	0.0256
Exchange Rate $_t$	-0.328210	0.081748	-4.014872	0.0003
R-Squared	0.892667	Mean Dependent Variable		0
Adjusted R-Squared	0.835843	S.D. Dependent Variable		0.128211
Standard Error of Regression	0.051946	Durbin-Watson Statistic		2.020353
Sum of Squared Residuals	0.045873			

not statistically significant, perhaps due to multicollinearity. The correlation coefficient between population and the time trend is 0.996, and the coefficient on population is statistically significant at the 10% level when time is omitted from the specification. Multicollinearity may also exist between these two variables and vehicle registrations because the correlation coefficient is 0.964 in both cases. This multicollinearity may explain why the coefficient of determination is relatively high for Laredo despite the apparent statistical insignificance of several explanatory variables.

A 10% increase in pedestrian border crossings is expected to increase transit ridership by 6.5% in Brownsville and by 1.6% in Laredo. Although the transit systems in both cities are accessible to pedestrian border crossers, on average there are twice as many such pedestrians per transit trip in Brownsville as in Laredo. The larger flow of cross-border pedestrian traffic relative to transit ridership partially accounts for the much larger elasticity of demand with respect to border crossings in Brownsville. One reason that more pedestrians cross into Brownsville than Laredo is that Matamoros, the Mexican city south of Brownsville, is much larger than Nuevo Laredo, the city situated opposite Laredo.

Border region transit operators could potentially capitalize on the positive relationship between border crossings and transit ridership by facilitating access to transit by visitors crossing through the ports of entry. For example, it may be possible to attract additional pedestrian border crossers by increasing the density of routes or the frequency of service near ports of entry. Bus terminals and other transit nodes can be located near border crossings to facilitate speedy access to a broader array of potential destinations within the city, including shopping centers. In order to attract additional passengers from Mexico, border area bus operators could follow the examples of numerous regional businesses and allow fares and passes to be purchased using pesos (Yoskowitz and Pisani 2007, Muñoz et al. 2011). Lastly, transit operators should take cross-border economic conditions into account when setting the levels of fare and service.

The exchange rate does not register a statistically significant impact on ridership in Brownsville. In Laredo, on the other hand, a strong negative relationship exists between the exchange rate and transit ridership. This shows that transit patronage in Laredo declines when the peso is weak relative to the dollar. The most likely explanation for this phenomenon is that Mexican nationals respond to an increase in the exchange rate by curbing cross-border shopping excursions and, therefore, reduce their utilization of Laredo's transit system. This is consistent with previous findings that shopping motivates the largest number of border crossings by pedestrians and others on the United States–Mexico border (Charney and Pavlakovich-Kochi 2002, Ghaddar and Brown 2005).

The negative relationship between the real exchange rate index and Laredo transit ridership raises the question of whether an improvement of economic conditions in Mexico is associated with more transit trips in Laredo. Although a weak peso may tend to increase manufacturing employment in Nuevo Laredo (Cañas et al. 2007), it also tends to reduce dollar-denominated wages in Mexico, and sharp peso depreciations often correspond to economic downturns. If residents of Mexico make fewer transit trips in Laredo during economic downturns and increase their utilization of the transit system during economic recoveries, this implies that transit is a normal good for those cross-border visitors. In contrast, the coefficient on the unemployment variable implies that transit is an inferior good for residents of Laredo. Border region transit authorities should consider the possibility that local and cross-border transit users may respond differently to cyclical changes in local economic performance.

The validity of the foregoing interpretation of the parameter estimates depends on the assumption that the residuals are not auto-correlated. Although the respective Durbin-Watson statistics are 2.02 and 2.05, the sample size is too small to definitively accept or reject the null hypothesis of no first-order serial correlation. Residual Q-statistics are calculated for up to 12 lags using both Box-Pierce and Ljung-Box methodologies (Lütkepohl and Krätzig 2004). The null hypothesis that the residuals are not autocorrelated up to lag 12 cannot be rejected at the commonly acceptable significance level of 0.05, implying that the error terms are not serially correlated.

CONCLUSION

The demand for public transportation in Brownsville and Laredo follows many, though not all, of the patterns observed in other regions. For example, ridership is inelastic with respect to both the level of service and fares, as in many other areas. Although some empirical evidence indicates that proportional increases in the level of service and fares will substantially increase ridership, this does not seem to hold for Laredo or Brownsville. Increasing fares and service proportionally appear to have small net effects on Brownsville ridership and a negative effect on Laredo ridership. The regression results also indicate that, as in other regions, public transportation and travel by private automobile are substitutes. Increases in gasoline prices and decreases in vehicle registrations generate positive, but less-than-proportional, changes in transit ridership in Brownsville and Laredo.

After controlling for other factors affecting transit demand, cross-border pedestrian traffic has a positive effect on transit ridership in Brownsville and Laredo. This relationship suggests that public transportation provides enhanced mobility to pedestrian visitors from Mexico, many of whom cross the border for the purpose of shopping. Similar to the retail sector, Laredo transit patronage increases when the peso appreciates and decreases when the purchasing power of the peso falls. In combination, these results suggest that public transit helps connect pedestrian border crossers with destinations such as retail outlets located on the north side of the international boundary.

While existing studies describe the role of public transportation in providing access to jobs for people who do not own an automobile, there has been little research into the role of transit in facilitating cross-border shopping. Additional research is needed to establish whether transit can directly benefit border city retail sectors by transporting foreign shoppers. It is also important to know whether the inspection process at ports of entry has a direct bearing on modal choice. There are times when vehicle wait times are longer than pedestrian wait times at Texas ports of entry. In response, some border crossers opt to walk across the border. Public transit routes and schedules can be modified to reflect this general pattern.

References

Blackley, P.R. “Spatial Mismatch in Urban Labor Markets: Evidence from Large U.S. Metropolitan Areas.” *Social Science Quarterly* 71 (1), (1990): 39-52.

BEA. “Regional Economic Information System.” Bureau of Economic Analysis. http://www.bea.gov/regional/reis, August 1, 2011.

BLS. “Local Area Unemployment Statistics.” Bureau of Labor Statistics. http://www.bls.gov/lau, May 18, 2011.

Bresson, G., J. Dargay, J.-L. Madre, and A. Pirotte. “Economic and Structural Determinants of the Demand for Public Transport: An Analysis on a Panel of French Urban Areas Using Shrinkage Estimators.” *Transportation Research Part A* 38 (4), (2004): 269–285.

BTS. “North American Border Crossing/Entry Data.” Bureau of Transportation Statistics. http://www.bts.gov/programs/international/transborder/TBDR_BC/TBDR_BC_Index.html, August 8, 2011.

Cañas, J., T.M. Fullerton, and W.D. Smith. “Maquiladora Employment Dynamics in Nuevo Laredo.” *Growth and Change* 38 (1), (2007): 23-38.

Cervero, R. “Transit Pricing Research: A Review and Synthesis.” *Transportation* 17 (2), (1990): 117-139.

Charney, A.H. and V.K. Pavlakovich-Kochi. "The Economic Impacts of Mexican Visitors to Arizona: 2001." Working Paper, Economic and Business Research Program, University of Arizona, 2002.

Chiang, W.C., R.A. Russell, and T.L. Urban. "Forecasting Ridership for a Metropolitan Transit Authority." *Transportation Research Part A* 45 (7), (2011): 696-705.

Coronado, R.A. and K.R. Phillips. "Exported Retail Sales Along the Texas-Mexico Border." *Journal of Borderlands Studies* 22 (1), (2007): 19-37.

Dallas Morning News. *Texas Almanac*. Dallas Morning News, Dallas, TX, 1984-86 and 2008-09 (multiple volumes).

Dargay, J.M. and M. Hanly. "The Demand for Local Bus Services in England." *Journal of Transport Economics and Policy* 36 (1), (2002): 73-91.

Dascher, K. and A. Haupt. "The Political Economy of Regional Integration Projects at Borders Where Poor and Rich Meet: The Role of Cross-Border Shopping and Community Sorting." *Journal of Urban Economics* 69 (1), (2011): 148-164.

Davidson, R. and J.G. MacKinnon. "Testing for Consistency Using Artificial Regressions." *Econometric Theory* 5 (3), (1989): 363-384.

De Leon, M., T.M. Fullerton, and B.W. Kelley. "Tolls, Exchange Rates, and Borderplex International Bridge Traffic." *International Journal of Transport Economics* 36 (2), (2009): 55-80.

de Rus, G. "Public Transport Demand Elasticities in Spain." *Journal of Transport Economics and Policy* 24 (2), (1990): 189-201.

EIA. "Retail Motor Gasoline and On-Highway Diesel Fuel Prices." Energy Information Administration. http://www.eia.gov/emeu/aer, May 16, 2011.

FRB. "Consumer Price Index – All Urban Consumers." Federal Reserve Bank of St. Louis. http://research.stlouisfed.org/fred2/, May 17, 2011.

Fernandez, R.B. "A Methodological Note on the Estimation of Time Series." *Review of Economics and Statistics* 63 (3), (1981): 471-476.

Frankena, M.W. "The Demand for Urban Bus Transit in Canada." *Journal of Transport Economics and Policy* 12 (3), (1978): 280-303.

Friedman, M. "The Interpolation of Time Series by Related Series." *Journal of the American Statistical Association* 57 (300), (1962): 729-757.

Fullerton, T.M. "Currency Movements and International Border Crossings." *International Journal of Public Administration* 23 (5-8), (2000): 1113-1123.

Ghaddar, S. and C.J. Brown. "The Economic Impact of Mexican Visitors Along the U.S.-Mexico Border: A Research Synthesis." Working Paper, Center for Border Economic Studies, University of Texas – Pan American, 2005.

Gkritza, K., M.G. Karlaftis, and F.L. Mannering. "Estimating Multimodal Transit Ridership with a Varying Fare Structure." *Transportation Research Part A* 45 (2), (2011): 148-160.

Giermanski, J.R. "NAFTA and the South Texas Border: Is the Border Fit to Compete?" *Journal of the Southwest* 39 (2), (1997): 287-302.

Heisz, A. and G. Schellenberg. "Public Transit Use Among Immigrants." *Canadian Journal of Urban Research* 13 (1), (2004): 170-191.

Herzog, L.A. "The Transfrontier Organization of Space Along the U.S.-Mexico Border." *Geoforum* 22 (3), (1991): 255-269.

Holmgren, J. "Meta-Analysis of Public Transport Demand." *Transportation Research Part A* 41 (10), (2007): 1021–1035.

Hughes, M.A. "Employment Decentralization and Accessibility." *Journal of the American Planning Association* 57 (3), (1991): 288-298.

Janes, J. "New Buses Complete System's Makeover." *The Monitor* (McAllen, TX), 20 June, 2011.

Kain, J.F. and Z. Liu. "Secrets of Success: Assessing the Large Increases in Transit Ridership Achieved by Houston and San Diego Transit Providers." *Transportation Research Part A* 33 (7-8), (1999): 601-624.

Lane, B.W. "The Relationship Between Recent Gasoline Price Fluctuations and Transit Ridership in Major U.S. Cities." *Journal of Transport Geography* 18 (2), (2010): 214–225.

Lovell, M.C. "A Simple Proof of the FWL Theorem." *Journal of Economic Education* 39 (1), (2008): 88-91.

Lütkepohl, H. and M. Krätzig. *Applied Time Series Econometrics*. Cambridge University Press, Cambridge, 2004.

Muñoz, R.A., M.J. Pisani, and T.M. Fullerton, Jr. "Exchange Rate Premia and Discounts for Retail Purchases Using Mexican Pesos in El Paso, Texas." *Social Science Journal* 48 (4), (2011): 612–620.

Nizlek, M.C. and L. Duckstein. "A System Model for Predicting the Effect of Energy Resources on Urban Modal Split." *Transportation Research* 8 (4-5), (1974): 329 – 334.

NTD. "Individual Profiles for all Transit Agencies in Urbanized Areas Over and Under 200,000 Population." National Transit Database. http://www.ntdprogram.gov/ntdprogram/data, August 15, 2011.

Patrick, J.M. and W. Renforth. "The Effects of the Peso Devaluation on Cross-Border Retailing." *Journal of Borderlands Studies* 11 (1), (1996): 25-41.

Paulley, N., R. Balcombe, R. Mackett, H. Titheridge, J. Preston, M. Wardman, J. Shires, and P. White. "The Demand for Public Transport: The Effects of Fares, Quality of Service, Income and Car Ownership." *Transport Policy* 13 (4), (2006): 295–306.

Peng, Z.R., K.J. Dueker, J. Strathman, and J. Hopper. "A Simultaneous Route-Level Transit Patronage Model: Demand, Supply, and Inter-Route Relationship." *Transportation* 24 (2), (1997): 159-181.

Pham, L.H. and J. Linsalata. *Fare Elasticity and its Application to Forecasting Transit Demand*. American Public Transit Association, Washington, DC, 1991.

Pindyck, R.S. and D.L. Rubinfeld. *Econometric Models and Economic Forecasts, 4th Edition*. Irwin McGraw-Hill, Boston, MA, 1998.

Romilly, P. "Subsidy and Local Bus Service Deregulation in Britain: A Re-Evaluation." *Journal of Transport Economics and Policy* 35 (2), (2001): 161-193.

Small, K.A. "Economics and Urban Transportation Policy in the United States." *Regional Science and Urban Economics* 27 (6), (1997): 671-691.

Taylor, B.D., D. Miller, I. Hiroyuki, and C. Fink. "Nature and/or Nurture? Analyzing the Determinants of Transit Ridership Across U.S. Urbanized Areas." *Transportation Research Part A* 43 (1), (2009): 60–77.

TDHPT. *Plans for Public Transportation in Texas.* Texas Department of Highways and Public Transportation, Austin, TX, 1979.

TDT. *DISCOS: District and County Statistical Data*. Texas Department of Transportation, Austin, TX, 1987-95 (multiple volumes).

TTS. *Texas Transit Statistics*. Texas Department of Transportation, Austin, TX, 1983-2009 (multiple volumes).

TDT. "Vehicle Registration Statistics." Texas Department of Transportation. http://www.txdot.gov/txdot_library/publications/stats.htm, May 17, 2011.

TEC. *Texas Labor Market Review*. Texas Employment Commission, Austin, TX, 1983-89 (multiple volumes).

Wang, H.K. and D. Skinner. "The Impact of Fare and Gasoline Price Changes on Monthly Transit Ridership: Empirical Evidence from Seven US Transit Authorities." *Transportation Research Part B* 18 (1), (1984): 29-41.

U.S. Census Bureau. "2005-2009 American Community Survey 5-Year Estimates." U.S. Census Bureau. http://factfinder.census.gov/home/saff/, September 5, 2011.

UTEP. "Border Region Modeling Project Data." University of Texas at El Paso. http://academics.utep.edu/border/. Accessed May 16, 2011.

Yoskowitz, D. W. and M.J. Pisani. "Risk and Reward: Currency Substitution and Acceptance of the Mexican Peso by Firms in the United States Southern Frontier." *Quarterly Review of Economics and Finance* 47 (3), (2007): 422–434.

Zellner, A. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistical Association* 57 (298), (1962): 348-368.

Acknowledgements

Partial financial support for this study was provided by Hunt Communities, El Paso Water Utilities, Texas Department of Transportation, JPMorgan Chase Bank of El Paso, the James Foundation Scholarship Fund, and the UTEP College of Business Administration Faculty Research Grant Fund. Helpful comments were provided by Sal Hernandez, Roberto Coronado, and Doyle Smith. Joe Aguilar of U.S. Customs and Border Protection provided border crossing/entry data for Laredo and Brownsville. Econometric research assistance was provided by Francisco Pallares and Carlos Morales.

Thomas Fullerton *is the JPMorgan Chase professor of economics & finance at UTEP. Prior experience includes positions as economist in the Executive Office of the Governor of Idaho, international economist in the Latin America Service of Wharton Econometrics, and senior economist at the Bureau of Economic and Business Research at the University of Florida.*

Adam Walke *holds an M.S. in economics from UTEP, where he studied as a James Foundation Scholar. He has published research on border region economic growth patterns, residential electricity consumption, and business cycle prospects in Mexico.*

High Occupancy Toll lane Performance Under Alternative Pricing Policies

by Thomas Light

This paper explores how alternative pricing and operating policies influence revenue generation, level of service, and travel time costs for high occupancy toll (HOT) lane facilities. A framework for modeling HOT lanes is applied to a hypothetical facility. The analysis suggests that the way in which tolls are set can have a non-trivial influence on competing measures of HOT lane performance. Other operating characteristics, such as the number of lanes designated as free and priced and whether carpools are allowed to ride free or must pay a toll to access the HOT lanes, are shown to significantly influence performance as well.

INTRODUCTION

High occupancy toll (HOT) lanes are receiving increased attention in the United States, in part because of their potential to better utilize scarce road capacity, but also because they raise revenue that can support investments in transportation systems. Versions of the HOT lane concept have been implemented on a number of highways, including Interstate 15 (I-15) in San Diego, California; Interstate 394 (I-394) near Minneapolis, Minnesota; State Route 167 (SR-167) near Seattle, Washington; and State Route 91 (SR-91) in Orange County, California. These facilities allow high occupancy vehicles (HOVs) to utilize the HOT lanes for free (or at a discount) and single occupant vehicles (SOVs) to access the HOT lanes by paying tolls that potentially vary by time of day and day of the week or with real-time traffic conditions. SOVs which opt not to pay the tolls can use free general purpose (GP) lanes that run parallel to the HOT lanes.

A review of existing HOT lane facilities suggests that their performance can vary widely, particularly in terms of their abilities to generate revenue. Factors that can influence the revenue generated by these facilities include the level of congestion and users' willingness to pay, as well as design features such as the share of capacity that is HOT, the way carpools are treated for the purpose of pricing, how tolls are determined, and whether or not the facility is priced dynamically or according to a static toll schedule. This paper seeks to understand how some of these design features influence the performance of HOT lane facilities with emphasis on the implications of setting tolls to achieve different goals (i.e., maximize revenue or maintain a target level of service). To do this, a simple but relatively flexible HOT lane model is presented and examined numerically.

The model considers a highway during a peak period in one direction with a fixed number of HOVs and SOVs using it. Users of the vehicles in the HOV and SOV classes vary in their value of travel time. In the model, as long as the HOT lanes offer travel time savings, carpools will use them since there is no access cost. Drivers of SOVs, however, choose between the GP and HOT lanes, with those having the highest value of time opting to pay the toll to access the HOT lanes.

This paper builds on Light (2009) where motorists vary in their value of time and choose between a priced and free route but only one vehicle class is considered. Toll and capacity policies, as well as the fiscal implications of pricing the facility to maximize welfare are explored and characterized. The distributional implications of adopting pricing on one route are also explored. Two clear results arise for the case when road capacity is the same before and after pricing is implemented and the transportation authority's budget is balanced via a uniform tax paid by all travelers: (1) value pricing will make some users worse off and (2) the user who is left worst off

is the one who is indifferent between using the priced and free alternative. Unlike Light's (2009) previous research, this analysis incorporates carpools into the model and explores the implications of a larger set of pricing objectives. The findings and methodology of this paper are likely to interest practitioners involved in evaluating HOT lanes. In particular, the model is relatively simple to set up and solve and relies on a limited set of assumptions. Because it is capable of predicting conditions under a broad set of HOT lane policies, it is appropriate for sketch planning revenue estimation and operational analysis.

The results of the numerical example suggest some generalizations about the efficiency and revenue potentials of HOT lanes that do not depend on facility design features, including the ways the tolls are set. Consistent with other research (Small and Yan 2001, and Verhoef and Small 2004), it is found that tolls that maximize revenue are higher than those that minimize aggregate travel time cost and produce large speed differences between GP and HOT lanes, all else equal. Additionally, it is found that tolls that are set to maintain a target level of service in the HOT lanes may be set above or below the toll that meets other objectives, depending on corridor demand and other factors.

The paper proceeds as follows. The next section discusses the different motivations for adopting HOT lanes in the United States, and describes four existing HOT lane facilities. Next, the theoretical model is presented followed by the results of the numerical analysis.

HOT LANES IN THEORY AND PRACTICE

Economists have focused on the potential ability for road pricing to improve the efficiency of road networks by causing motorists to internalize the externalities they impose on other motorists and the public at large. The delay costs imposed on others from a vehicle's contribution to congestion is the primary external cost discussed in the congestion pricing literature. However, other external costs such as those associated with accidents, emissions, and noise can be incorporated into congestion pricing. HOT lanes represent a relatively dull instrument for inducing the internalization of vehicle externalities since, in most applications, relatively few travelers in HOT lane corridors actually pay a toll. Small et al. (2006) have noted that HOT lanes have the potential to improve the efficiency of urban highways by making better use of underutilized carpool lanes and providing faster and more reliable travel to those who value it most.

In practice, however, the recent attention given to HOT lanes is more likely due to their ability to generate revenue. As the costs of transportation improvements have escalated over time, funding for transportation has not kept up the pace. Many metropolitan areas are now looking for new ways to fund transportation improvements, including the implementation of HOT lanes. As an example, the San Francisco Bay Area is looking into converting the existing regional carpool lanes network into a network of HOT lanes with the revenues generated to be used to expand the HOT lane network in the future (Metropolitan Transportation Commission 2008).

In addition to these motivating reasons for adopting HOT lanes, the HOT lane concept is attractive because it continues to encourage carpooling by granting carpools preferential access to a faster travel option. This is particularly important given the recent evidence that HOV lanes may not be an efficient means of reducing traffic congestions (Dahlgren 1998, Poole and Balaker 2005), making HOT lanes a more appealing alternative. In order to encourage carpool formation, it has been suggested that tolls should be set high enough to maintain a high minimum level of service in the HOT lanes. Furthermore, in California and other states, there can be legal restrictions which place level of service requirements on HOT lanes. For instance, the legislation enabling the development of the I-15 HOT lane in San Diego requires that a level of service B or Caltrans HOV lane standard be maintained in the I-15 HOT lanes (Turnbull 1997). This requires speeds in the I-15 HOT lanes to meet or exceed 45 miles per hour.

Small and Yan (2001) extend a model first developed by Liu and McDonald (1998) to account for user heterogeneity on a facility resembling SR-91. They highlight the importance of accounting

for user heterogeneity in preferences for travel time savings when determining the benefits of HOT lane pricing. Small and Yan (2001) simulate both welfare maximizing and revenue maximizing tolls for facilities that have priced lanes running parallel to free GP lanes. Their findings suggest that revenue maximization is likely to produce significantly higher tolls than welfare maximization and may result in poorer outcomes than if the priced lanes were converted to free GP lanes.

Sullivan and Burris (2006) conduct a benefit cost analysis for the SR-91 Express Lane facility. Their analysis suggests that the facility produces benefits that are greater than the amortized investment and operating costs. Their analysis also indicates that the majority of benefits from the SR-91 Express Lane facility come about through travel time savings as opposed to reductions in fuel use or emissions. Safirova et al. (2007) studied the impacts of converting existing HOV lanes to HOT lanes in Washington, D.C.[1] Their analysis assumes that tolls are set to maximize aggregate social welfare. Their findings suggest that while all income groups benefit from the conversion to HOT lanes, higher-income households tend to see the greatest welfare gains. Small et al. (2006) studied a variety of HOT lane pricing policies using a model estimated from data collected for SR-91 in Orange County, California. Similar to Safirova et al. (2007), they find that the highest-income users of the corridor tend to benefit more than lower-income users when HOT lane pricing is adopted.

Design and Performance of Four HOT Lane Facilities

Because of the many appealing features of HOT lanes, there are numerous examples of their use, four of which are briefly discussed below.[2]

Interstate 15 (San Diego, California). The I-15 HOT lanes consist of two reversible lanes that are approximately eight miles in length. Construction is underway to extend the facility and add two additional HOT lanes. Currently, the toll for SOVs varies dynamically with congestion in the HOT lanes and is updated every six minutes. Message signs near the access point to the HOT lanes indicate the charge, which typically varies between $0.50 and $4.00, although it may be as high as $8.00 in periods of high demand. Carpools with two or more passengers can use the I-15 HOT lanes for free.

Interstate 394 (Minneapolis, Minnesota). The I-394 MnPASS facility allows vehicles with two or more persons to travel free while SOVs may access the HOT lanes if they pay a toll. The facility is dynamically priced. A three-mile stretch of it consists of two reversible lanes that accommodate peak direction traffic, while the remainder consists of one lane in each direction.

State Route 167 (Seattle, Washington). The SR-167 HOT lane facility opened in 2008 and is located near Seattle, Washington. The SR-167 HOT lanes allow vehicles with two or more occupants (HOV 2+) to use it free while SOV must pay a toll to access the lanes. The facility is dynamically priced every five minutes using real-time traffic data on speed and volumes, with tolls varying between $0.50 and $9.00. Motorists who wish not to use the HOT lane can use two parallel GP lanes that operate in each direction.

State Route 91 (Orange County, California). The SR-91 Express Lane facility was constructed as part of a private, for profit toll road venture authorized by the California Legislature in 1989. However, the Orange County Transportation Authority subsequently took control of the facility after its first three years of operation. While all vehicles are charged a toll during peak periods on the 10-mile State Route 91 Express Lane facility, vehicles with three or more occupants receive a 50% discount on the toll charge. The toll varies by time of day and day of the week according to a fixed schedule.

The I-15, I-394, and SR-167 facilities all operate under an HOV 2+ policy and utilize dynamic pricing algorithms to adjust toll levels based on real-time traffic conditions. Because the tolling algorithms are proprietary, it is unclear how they work and what they are designed to achieve. However, it is known that their algorithms have minimum and maximum tolls as well as a mechanism to adjust the toll so that specified HOT lane level-of-service requirements are not breached. SR-91 is unique in that it charges all vehicles during peak hours and uses a static toll schedule, which is updated every few months.

Perhaps the most striking performance feature of these examples is the range of revenue generation. Despite all four facilities being of fairly similar length, Table 1 suggests SR-91 is much more profitable than the others, with over $43 million in gross toll revenues generated during 2009.[3] I-15 and I-394 generate revenues of approximately $1 million annually while SR-167 produced only $0.3 million in its initial year of operations. The differences in revenue are at least partly due to the treatment of carpool vehicles for the purposes of tolling, as well as the number of priced lanes, the level of congestion in the corridor, and differences in willingness-to-pay of motorists. The model presented in the next section can potentially accommodate variation in these facility features as well as different approaches in setting toll levels.

Table 1: Description and Performance of Four Facilities

	I-15 (San Diego, CA)	**I-394 (Minneapolis, MN)**	**SR-167 (Seattle, WA)**	**SR-91 (Orange County, CA)**
Year Opened	1997	2005	2008	1995
Distance	8 miles	11 miles	11 miles northbound/ 9 miles southbound	10 miles
Number of GP Lanes	4 lanes in each direction	2 lanes in each direction	2 lanes in each direction	4/5 lanes in each direction
Number of HOT Lanes	2 reversible lanes	1 lane in each direction for 8 miles, 2 reversible lanes for 3 miles	1 lane in each direction	2 lanes in each direction
Carpool Policy	HOV 2+ ride free	HOV 2+ ride free	HOV 2+ ride free	HOV 3+ ride free during off-peak/ HOV 3+ pay discounted toll during peak
Pricing Approach	Dynamically Priced	Dynamically Priced	Dynamically Priced	Static Toll Schedule
Hours/Days of Operation	12.5 hours per day/ 5 days per week	9 hours per day/ 5 days per week	14 hours per day/ 7 days per week	24 hours per day/ 7 days per week
Annual Gross Revenue	Approximately $1.2 million (2007)	Approximately $1.0 million (2007)	$0.3 million (2008)	$43.7 million (2009)

Source: Washington State Department of Transportation (2009), Orange County Transportation Authority (2009), Cambridge Systematics (2002), Federal Highway Administration (2007), Federal Highway Administration (undated).

THE MODEL

The model considers one direction of a highway facility that is divided into GP and HOT lanes. It applies to a single period (say a typical peak hour or perhaps a five-minute period if dynamic pricing is implemented) in which N_S SOVs and N_C HOVs utilize the facility.[4] Each vehicle is associated with a value of time, $v \in [\underline{v}, \overline{v}]$, which varies from one vehicle to the next. The fraction of SOVs and HOVs with a value of time less than or equal to v is given by $F_S(v)$ and $F_C(v)$, respectively.

Both the GP and HOT lanes are congestible. The amount of time it takes to travel in the GP and HOT lanes is given by $t_G(x_G)$ and $t_H(x_H)$, respectively, where x_G and x_H denote the number of vehicles using the GP and HOT lanes and $x_G + x_H = N_S + N_C$. The travel time functions are assumed to be increasing and strictly convex. Furthermore, it is reasonable to assume that $t_G(0) = t_H(0)$ since a free flowing HOT lane should operate at about the same speed as a parallel, free flowing GP lane, although this assumption can be relaxed without impacting the modeling.

Under the base case HOT lane policy, the tolling authority allows HOVs to use the HOT lanes at no cost while SOVs must pay a toll $p > 0$ to access the HOT lanes. The equilibrium condition requires that no driver can change his or her lane choice and be made better off given the choices of other drivers. That is, drivers choose the travel option that minimizes their generalized cost of travel in equilibrium. This implies that a SOV with value of time v will select the HOT lane if $vt_H^* + p < vt_G^*$ and the GP lanes if $vt_H^* + p > vt_G^*$ where t_G^* and t_H^* represent the equilibrium travel times in the GP and HOT lane respectively. An SOV is indifferent between the two alternatives if $vt_H^* + p = vt_G^*$. If it is optimal for SOV users with value of time v to choose the HOT lanes, it must be optimal for all SOV users with a value of time greater than v to choose the HOT lane as well. Similarly, if SOV users with value of time v do not choose the HOT alternative, all SOVs with a value of time less than v must also choose the GP lanes. Carpoolers are exempt from paying the toll and therefore are only concerned with the relative travel times in the GP and HOT lanes. They will use the HOT lane as long as $t_H^* < t_G^*$ and will be indifferent between these two options if $t_H^* = t_G^*$.

Three types of equilibrium can occur depending on the SOV and HOV volumes and the toll level that is selected by the tolling authority. In Case 1, if travel times in the HOT lanes are greater than in the GP lanes when all SOVs use the GP lanes and all HOVs use the HOT lanes (which implies that, $t_G(N_S) \geq t_H(N_C)$), then regardless of how the toll is set, a pooling equilibrium occurs in which all SOVs stay in the GP lanes and carpool vehicles allocate themselves to the GP and HOT lane until travel times equalize (i.e., $t_H^* = t_G^*$). In Case 2, if travel times in the HOT lane are less than in the GP lanes when all SOVs use the GP lanes and all HOVs use the HOT lanes (which implies that $t_G(N_S) > t_H(N_C)$) and the toll is set such that the SOV driver with the highest value of time would find it advantageous to buy his or her way into the HOT lanes (i.e., $p \in (0, \overline{v}(t_G(N_S) - t_H(N_C))]$), a separating equilibrium occurs in which all HOVs use the HOT lane and the SOV users with the highest value of time pay the toll to use the HOT lane. Specifically, all SOVs with a value of time greater than (less than) $\hat{v}$ use the HOT (GP) lanes, where $\hat{v}$ solves,

$$(1) \quad \hat{v}t_G(N_S F_S(\hat{v})) = \hat{v}t_H(N_C + N_S(1 - F_S(\hat{v}))) + p.$$

Here $\hat{v}$ represents the value of time of the SOV users who are indifferent between using the GP lane and paying the toll to use HOT lanes in equilibrium. In Case 3, if travel times in the HOT lanes are less than in the GP lanes when all SOVs use the GP lanes and all HOVs use the HOT lanes (which implies that $t_G(N_S) > t_H(N_C)$ but the toll level is set so high that the SOV users with the highest value of time would not find it advantageous to buy their way into the HOT lanes (i.e., $p > \overline{v}(t_G(N_S) - t_H(N_C))$, then despite the fact that traffic in the HOT lanes are moving faster than in the GP lanes the toll is set so high that no SOV users will opt to use the HOT lane in equilibrium. Therefore, the HOT lane effectively operates like a carpool lane.

In Case 1, there are so many HOVs that speed in the HOT lanes degrades to the same level as in the GP lanes and no SOVs are willing to buy their way into the HOT lane. In practice, if a facility is operating in this state often, the tolling authority should consider converting the HOT lane to a GP lane, raising the carpool occupancy requirement, or converting a GP lane to a HOT lane so that there is additional HOT capacity. Case 2 is more interesting. In this case, the HOT lane is used by all carpools and, by the highest value of time, SOV users. The total number of vehicles using the GP and HOT lanes is $x_G(\hat{v}) = N_S F_S(\hat{v})$ and $x_H(\hat{v}) = N_C + N_S(1 - F_S(\hat{v}))$, respectively. In Case 3, the HOT lane is made so expensive that no SOVs use it, so it effectively operates as a carpool lane. Throughout the rest of this paper, it is assumed that the facility is operating under the conditions of Case 2.

HOT Lane Pricing Policies

Having described equilibrium under HOT lane pricing, optimal toll policies are characterized next under three pricing objectives: minimizing the aggregate cost of travel, maximizing the revenue generated by the HOT lanes, and maintaining a target level of service in the HOT lanes. These toll setting problems can be formulated as mathematical programming problems.

When solving for optimal policies, it is helpful to note that there exists a unique toll $p > 0$ that will induce any feasible $\hat{v}$ in the equilibrium associated with Case 2. In particular, this toll ($p^e(\hat{v})$) can be found by rearranging Eq. (1) to get,

$$(2)\quad p^e(\hat{v}) = \hat{v}\left[t_G(N_S F_S(\hat{v})) - t_H(N_C + N_S(1 - F_S(\hat{v})))\right].$$

Notice that the range of marginal values of time that are feasible are defined by $\hat{v} \in (v^o, \overline{v}]$ where,

$$(3)\quad v^o = [v \in [\underline{v}, \overline{v}]: t_G(x_G(v)) = t_H(x_H(v))].$$

Here v^o represents the lowest feasible marginal value of time that can be induced by a strictly positive toll level. A marginal value of time will approach v^o as the toll level approaches zero. As this happens, travel times on the GP and HOT lanes will also converge.

Minimizing Aggregate Travel Time Cost. Under this pricing policy, the tolling authority seeks to minimize the aggregate travel time cost in the corridor. Since total demand for travel on the highway is assumed perfectly inelastic, the welfare of motorists in the model will vary with the time and monetary cost of completing trips. Under the additional assumption that toll revenues are returned to motorists as lump-sum transfers, minimizing aggregating travel time costs will be consistent with welfare maximization.[5]

Aggregate travel time cost in the corridor can be broken down into the travel time costs of GP ($C_G(\hat{v})$) and HOT ($C_H(\hat{v})$) lane users, which are respectively calculated as,

$$(4)\quad C_G(\hat{v}) = t_G(x_G(\hat{v})) \times x_G(\hat{v}) \times \frac{\int_{\underline{v}}^{\hat{v}} v dF_S(v)}{F_S(\hat{v})}$$

$$(5)\quad C_H(\hat{v}) = t_H(x_H(\hat{v})) \times N_S(1 - F_S(\hat{v})) \times \frac{\int_{\hat{v}}^{\overline{v}} v dF_S(v)}{1 - F_S(\hat{v})} + t_H(x_H(\hat{v})) \times N_C \times \int_{\underline{v}}^{\overline{v}} v dF_C(v)$$

The above expressions for aggregate travel time cost reflect the fact that SOVs sort between the GP and HOT lanes based on their value of time, with all SOVs with a value of time less than $\hat{v}$ opting to use the GP lanes and all those SOVs with a value of time greater than $\hat{v}$ opting to purchase their way into the HOT lanes. The sorting of SOVs affects the calculation of both the number of SOVs using the GP and HOT lanes, and how their average value of time is calculated. Specifically, the aggregate travel time cost experienced in the GP lanes ($C_G(\hat{v})$) represents the product of the travel time in the GP lanes ($t_G(x_G(\hat{v}))$), the number of SOVs using the GP lanes ($x_G(\hat{v}) = N_S F_S(\hat{v})$), and the average value of time of SOVs who use the GP lanes ($\int_{\underline{v}}^{\hat{v}} v dF_S(v) \Big/ F_S(\hat{v})$).[6] The aggregate travel time cost associated with the HOT lanes ($C_H(\hat{v})$) can be decomposed into the aggregate travel time cost for SOV and HOV users of the HOT lanes. The aggregate travel time cost for the SOV users of the HOT lane is calculated as the product of the HOT lane travel time ($t_H(x_H(\hat{v}))$), the number of SOVs using the HOT lane ($N_S(1-F_S(\hat{v}))$), and the average value of time of SOVs using the HOT lane ($\int_{\hat{v}}^{\overline{v}} v dF_S(v) \Big/ (1-F_S(\hat{v}))$). The aggregate travel cost of the HOV users in the HOT lane is calculated as the product of the HOT lane travel time ($t_H(x_H(\hat{v}))$), the number of HOVs in HOT lane (N_C), and the average value of time of HOVs ($\int_{\underline{v}}^{\overline{v}} v dF_C(v)$). The aggregate travel time cost in both the GP and HOT lanes is $C(\hat{v})$ and it is equal to $C(\hat{v}) = C_G(\hat{v}) + C_H(\hat{v})$.

A tolling authority wishing to minimize aggregate travel time cost ($C(\hat{v})$) will want to induce through tolling a marginal value of time $\hat{v}*$ such that, $\partial C(\hat{v}*) / \partial \hat{v}* = 0$. The Appendix shows this derivative. Using this expression and the equilibrium implied by Eq. (2), the Appendix further shows that the toll that minimizes aggregate travel time cost equals the difference between the marginal external congestion cost (*MEC*) in the HOT and GP lanes. Specifically, this toll is,

$$(6) \quad p^* = MEC_H(\hat{v}^*) - MEC_G(\hat{v}^*)$$

Here,

$$(7) \quad MEC_G(\hat{v}) = \frac{\partial t_G(x_G(\hat{v}))}{\partial x_G(\hat{v})} \times x_G(\hat{v}) \times \frac{\int_{\underline{v}}^{\hat{v}} v dF_S(v)}{F_S(\hat{v})}$$

$$(8) \quad MEC_H(\hat{v}) = \frac{\partial t_H(x_H(\hat{v}))}{\partial x_H(\hat{v})} \times \left(N_S(1-F_S(\hat{v})) \times \frac{\int_{\hat{v}}^{\overline{v}} v dF_S(v)}{1-F_S(\hat{v})} + N_C \times \int_{\underline{v}}^{\overline{v}} v dF_C(v) \right)$$

are the marginal external congestion cost calculated for the GP and HOT lanes, respectively.[7] The *MEC* represents the monetized value of the congestion externality generated by a marginal increase in use in the GP or HOT lanes. The toll described by Eq. (6) cause motorists to internalize their contribution to congestion in the HOT and GP lanes when making a decision over which set of lanes to utilize. In particular, if a motorist opts to use the HOT lanes, he or she will increase the travel time cost experienced by other HOT lane users by $MEC_H(\hat{v}^*)$, but reduce travel time cost in the GP lanes by $MEC_G(\hat{v}^*)$. The toll that minimizes aggregate travel time cost causes SOVs to take both of these congestion related effects into account when deciding whether or not to use the HOT lanes.

Revenue Maximization: The second tolling approach seeks to maximize the revenue that will be generated by the HOT lane. This approach coincides with that which would likely be pursued by a private HOT lane operator. One might also observe a publicly owned HOT lane facility priced in this way if the operator is financially constrained.

Having defined the equilibrium pricing function in Eq. (2), it is possible to quantify the revenue raised by the HOT lane as a function of any feasible $\hat{v}$. In particular, the HOT lane revenue function is given by $R(\hat{v}) = N_S(1-F_S(\hat{v})) \times p^e(\hat{v})$. It represents the product of the number of users paying to use

the HOT lanes and the toll charge. If $\hat{v}^{**}$ is the solution to the revenue maximization problem, then the first order condition requires $\partial R(\hat{v}^{**})/\partial\hat{v}^{**}=0$. As shown in the Appendix, the first order condition implies that the revenue maximizing toll level will equal,

$$(9)\quad p^{**}=\frac{1-F_S(\hat{v}^{**})}{f_S(\hat{v}^{**})}\frac{\partial p^e(\hat{v}^{**})}{\partial\hat{v}^{**}}$$

Here, $f_S(\hat{v})=\partial F_S(\hat{v})/\partial\hat{v}$.

Maintain a Minimum Level of Service (LOS): Under the third objective, the HOT lane is priced so as to maintain a minimum level of service, which can be defined as the minimum speed in the HOT lane. Let $\tilde{s}$ be the desired minimum speed measured in miles per hours (mph). If travel time is measured in hours and the length of the facility in miles and equals *d*, then a tolling authority wishing to maximize use of the HOT lanes without exceeding the desired minimum speed will solve,

$$(10)\quad \max_{\hat{v}\in(v^o,\bar{v}]} x_H(\hat{v}) \text{ such that } \frac{d}{t_H(x_H(\hat{v}))}\geq\tilde{s}\,.$$

Let $\hat{v}^{***}$ represent a solution to Eq. (10). The price required to induce a HOT lane speed of $\tilde{s}$ is given by $p^{***}=p^e(\hat{v}^{***})$. In fact, any toll greater than or equal to p^{***} will induce a speed of at least $\tilde{s}$. For the purposes of the numeric example presented in the next section, it is assumed that the tolling authority sets a minimum level of service in the HOT lane that corresponds to a minimum speed of 50 mph (i.e., $\tilde{s}$ = 50 mph).

Notice that the goal of maintaining a minimum level of service can be combined with other objectives by simply incorporating the constraint in Eq. (10) into other toll optimization problems. For instance, one could solve for the toll that minimizes aggregate social cost or maximizes revenue subject to a minimum level of service constraint simply by introducing the constraints in Eq. (10) into the aggregate cost and revenue maximization equation, respectively.

A NUMERIC COMPARISON OF ALTERNATIVE PRICING OBJECTIVES

In this section, the relationships between the HOT lane toll level, aggregate travel time cost, revenue, and GP and HOT lane speed under different pricing objectives and facility design features are examined.

Specification of the Numeric Example

In order to examine numerically the implications of different tolling policies, vehicle and facility characteristics must be specified. It is assumed that the facility is 10 miles long (i.e. *d* = 10 miles) and originally operates with three GP lanes and one carpool lane in each direction. Also, it is assumed that the travel time functions are of the form suggested by the Bureau of Public Roads (1964). Specifically,

$$(11)\quad t(x)=\frac{10}{60}\left(1+0.20\left(\frac{x}{2{,}000k}\right)^4\right)$$

where *k* represents the number of GP or HOT lanes provided and *x* is the volume of vehicles using those lanes per hour. The implied free flow speed for this volume delay function is 60 miles per hour. The empirical evidence supporting the use of the BPR function is discussed in Small (1992). Next, it is assumed that there are 8,972 SOVs and 1,028 HOVs per hour. These traffic volumes

were selected to give speeds in the GP lanes and HOT lane of approximately 30 and 59 mph, respectively, when the HOT lane is operated as an HOV lane. Under these conditions, there could be advantages to converting the HOV lane to a HOT lane to relieve some congestion in the GP lanes. In sensitivity analysis, both the total corridor volume and the share of vehicles that are HOVs are varied. Finally, it is assumed that the value of time of SOVs and HOVs follow a log-normal distribution. The mean and standard deviation of SOVs' values of time are assumed to be $20/hour and $10/hour, respectively, while HOVs are assumed to have a mean value of time of $40/hour with a standard deviation of $20/hour. These value of time assumptions imply that the mean and standard deviations of the logarithms of values of time are 2.88 and 0.47 for SOVs and 3.58 and 0.47 for HOVs, respectively.

The mean SOV value of time assumption is in line with estimates from Small et al. (2005), who studied the State Route 91 Express Lane facility. As is the case in other similar studies, such as Sullivan and Burris (2006), HOVs are assumed to have a higher average value of time, due primarily to their higher vehicle occupancy. Hensher (2008) provides empirical evidence for this assumption and discusses some implications for toll road evaluations. Sensitivity analysis is conducted to illustrate how the results change when the mean HOV value of time is reduced to $30/hour.

In addition to the three alternative tolling objectives, three other changes to the facility are considered. The first deals with carpools. The implications of moving from a policy where carpools can use the HOT lanes for free to one where every vehicle must pay to use the HOT lanes are examined. This case is similar to the express lane concept on State Route 91 and may be appropriate if there is limited capacity to sell or if revenue generation becomes a priority. The second policy variation is with respect to the share of capacity provided as GP and HOT. In particular, the implications of converting an additional lane to HOT so that there are a total of two GP lanes and two HOT lanes operating in total in each direction in considered. The third and final policy considered involves converting the HOV lane to a GP lane, so that all four lanes on the highway operate as GP lanes. No revenue is generated in this case, but it serves as a useful benchmark for comparison.

Hot Lane Performance Under Alternative Scenarios

Table 2 summarizes the conditions under the carpool lane scenario, an all-GP lanes scenario, and nine different tolling conditions, carpool policy, and capacity scenarios. In all of the HOT lane scenarios except the eighth, which sets the toll to maximize revenue and converts one GP lane to a HOT lane, the HOT alternatives operate at a lower aggregate travel time cost than the carpool lane base case. In the three scenarios where aggregate travel time cost is minimized (Scenarios one, four, and seven), there is a 22% to 23% reduction in aggregate travel time cost relative to the HOV scenario. When there is only a small amount of capacity to sell, as is the case in the first through the third scenario, the different HOT lane pricing objectives perform similarly in terms of aggregate travel time cost. However, in the cases where there is more capacity to sell, there is greater variation in aggregate travel time cost between the scenarios. It is also interesting to note that the conversion of the HOT lane to a GP lane would produce considerable benefits as measured by the reductions in aggregate travel time costs.

In terms of revenue generation, the seventh through ninth scenarios show large differences between the pricing objectives. Revenue under the level of service objective are more than double those found under aggregate travel time cost minimization, while revenue maximization produces revenue which are four times larger than those associated with aggregate travel time cost minimization. These large differences in revenue generation across pricing objectives do not prevail when there is limited capacity to sell as is the situation in scenario one through three.

Under revenue maximization, toll levels tend to be much higher, which causes fewer motorists to pay to use the HOT lane. As a result, there is more congestion in the GP lanes while speed in the HOT lane remains near the free flow level. When aggregate travel time cost is minimized,

Table 2: Summary of Peak Hour Performance Under Alternative HOT Lane Policies

	HOV Lane	All GP Lanes	HOT Lane(s) Cost Min	HOT Lane(s) Rev Max	HOT Lane(s) Maintain LOS
			3 GP Lanes, 1 HOT Lane; HOVs Ride Free		
Scenario	*Base Case*		(*1*)	(*2*)	(*3*)
GP Volume (x_G)	8,972.0	10,000.0	7,787.1	8,248.7	8,000.0
HOV/HOT Volume (x_H)	1,028.0	NA	2,212.9	1,751.3	2,000.0
GP Speed (MPH)	30.0	40.3	38.3	35.0	36.8
HOV/HOT Speed (MPH)	59.2	NA	46.2	53.7	50.0
Marginal VoT ($\hat{v}$)	NA	NA	$30.32	$34.67	$32.06
Toll (*p*)	NA	NA	$1.35	$3.45	$2.31
Aggregate Travel Cost ($C(\hat{v})$)	$69,472	$54,725	$53,739	$55,842	$54,202
Toll Revenue ($R(\hat{v})$)	NA	NA	$1,603	$2,495	$2,245
			3 GP Lanes, 1 HOT Lane; HOVs Must Pay		
Scenario			(*4*)	(*5*)	(*6*)
GP Volume (x_G)			7,831.3	8,812.3	8,000.0
HOT Volume (x_H)			2,168.7	1,187.7	2,000.0
GP Speed (MPH)			38.0	31.1	36.8
HOT Speed (MPH)			47.0	58.5	50.0
Marginal VoT ($\hat{v}$)			$28.45	$35.42	$29.36
Toll (*p*)			$1.44	$5.35	$2.11
Aggregate Travel Cost ($C(\hat{v})$)			$53,593	$62,284	$53,954
Toll Revenue ($R(\hat{v})$)			$3,125	$6,350	$4,229
			2 GP Lanes, 2 HOT Lanes; HOVs Ride Free		
Scenario			(*7*)	(*8*)	(*9*)
GP Volume (x_G)			5,423.5	7,676.2	6,000.0
HOT Volume (x_H)			4,576.5	2,323.8	4,000.0
GP Speed (MPH)			35.8	16.2	29.8
HOT Speed (MPH)			44.7	58.7	50.0
Marginal VoT ($\hat{v}$)			$20.27	$29.52	$21.98
Toll (*p*)			$1.13	$13.23	$2.98
Aggregate Travel Cost ($C(\hat{v})$)			$53,484	$95,765	$55,902
Toll Revenue ($R(\hat{v})$)			$3,995	$17,150	$8,848

Notes: GP = general purpose; HOT = high occupancy toll; HOV = High occupancy vehicle; MPH = miles per hour; VoT = value of time; Cost Min = cost minimization; Rev Max = revenue maximization; Maintain LOS = maintain a minimum level of service.

there is less service differentiation between the GP and HOT lanes than is observed in revenue maximization. When the toll is set to maintain a specific level of service, the speed in the GP lanes varies inversely with the target HOT lane speed.

The finding that revenue maximization tends to result in higher tolls than would be efficient is consistent with Liu and McDonald (1998), Small and Yan (2001), and Verhoef and Small (2004). Public officials involved in the management of HOT lanes are likely to face a tradeoff between revenue generation and achieving travel time cost efficiency. Because aggregate travel time cost cannot be as easily measured as revenue, there is likely to be a natural tendency to put revenue generation above it.

Sensitivity of Results to Alternative Toll Levels

Figure 1 shows how aggregate travel time cost, revenue, and speed in the GP and HOT lanes vary as the toll is adjusted for the case where there are three GP lanes and one HOT lane, and carpools ride free in the HOT lane. This is the same capacity and carpool policy explored in scenario one through three. In the graphs, when the toll equals zero, the HOT lane effectively operates as a GP lane and speeds across the two lane types are the same. As the figure shows, there are modest benefits in terms of aggregate travel time cost reductions from HOT lane tolling. But, if the toll is set high, HOT lane capacity can be underutilized, causing the facility to operate worse in terms of aggregate travel time cost than if the HOT lane is simply converted to a GP lane. Figure 1 highlights the fact that the way in which HOT lanes are priced can have a non-trivial impact on the potential travel time benefits and revenue generated. As a consequence, considerable thought should go into selecting tolling algorithms and pricing parameters when implementing HOT lanes.

Sensitivity of Results to Alternative Demand Level

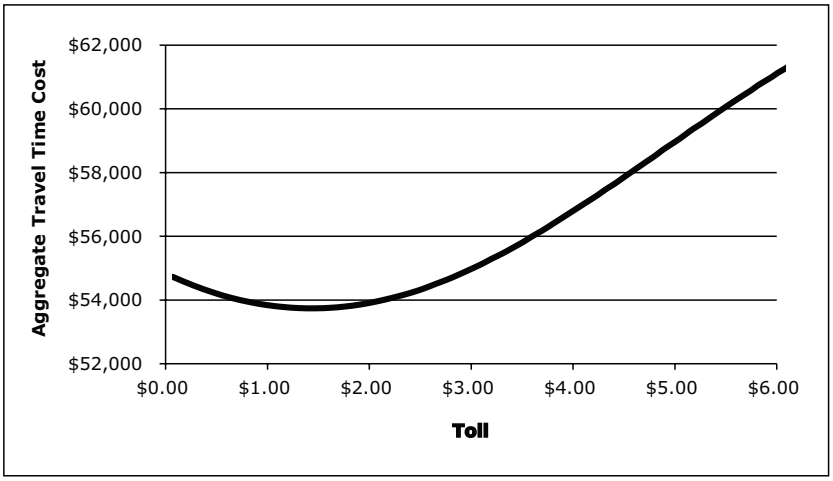
The estimates above are most likely representative of a facility operating under peak demand. In this section, demand is varied to illustrate how a HOT lane priced under different objectives might operate during other times of the day. To vary total corridor demand, it is assumed that the share of carpool vehicles remains constant at 10.2% of total vehicle demand. Let $N = N_S + N_C$ and rewrite $N_S = (1 - 0.102)N$ and $N_C = 0.102N$.

Figure 2 shows how tolls, aggregate travel time cost, and revenue vary with traffic volume under each pricing objective and the assumptions implicit in scenario one through three. Figure 3 extends Figure 2 to show GP and HOT lane speed. Under revenue maximization, the toll level tends to be about twice as high as the toll level that minimizes aggregate travel time cost. The toll that maintains a minimum HOT lane level of service behaves much differently. As shown in Figure 3, below 8,000 vehicles per hour (i.e., $N = 8{,}000$) the HOT lane effectively becomes a GP lane (i.e., $p = 0$) under the minimum HOT lane level of service objective and the speed in the GP lanes and HOT lane are equalized above the minimum required HOT lane speed of 50 miles per hour. When traffic volume exceeds 8,000 vehicles per hour, however, pricing keeps the HOT lane moving at 50 miles per hour.

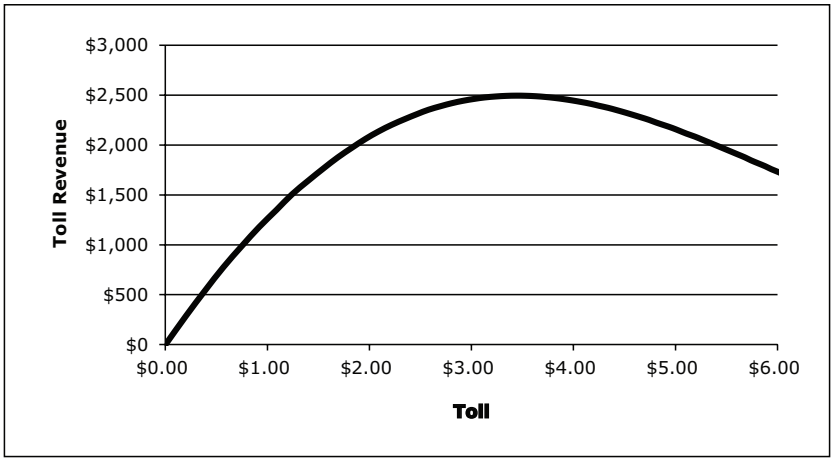
The second pane of Figure 2 shows how aggregate travel time cost varies under each objective and the case where the HOT lane is operated as an HOV lane. Interestingly, it is difficult to differentiate between the alternative HOT lane objectives in this graph. However, the HOV lane case lies above the HOT lane cases for all levels of traffic but most noticeably when corridor demand is highest. The bottom pane of Figure 2 illustrates revenue generation under each HOT lane pricing objective. Revenues under aggregate travel time cost minimization tend to be about 60% of that obtained under revenue maximization. The minimum level of service objective produces a discontinuous level of revenue for the reasons discussed above.

Figure 1: Relationship Between Toll Level and Aggregate Travel Time Cost, Revenue, and Speed in Scenarios 1–3 (3 GP Lanes, 1 HOT Lane; HOVs Ride Free)

(1)



(2)



(3)

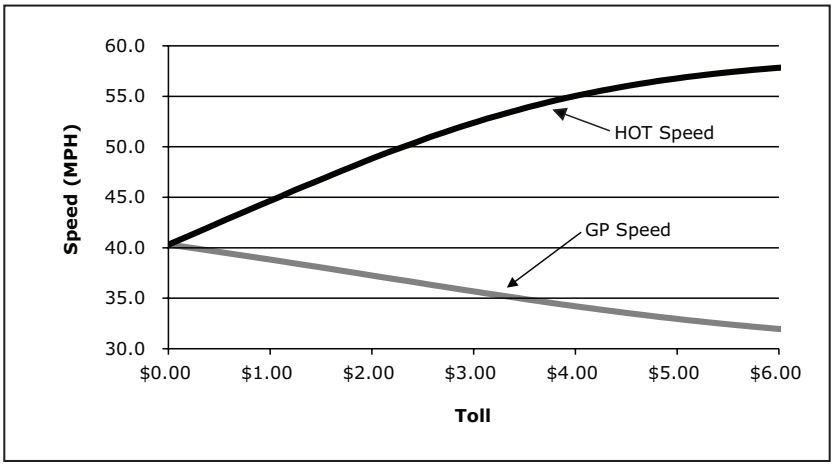
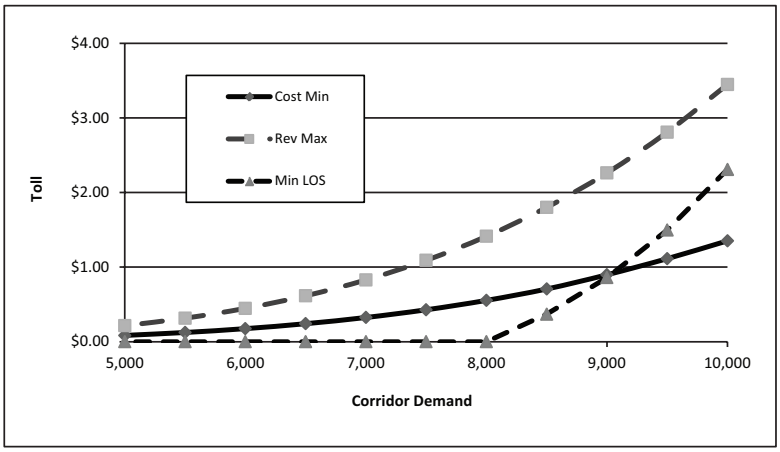
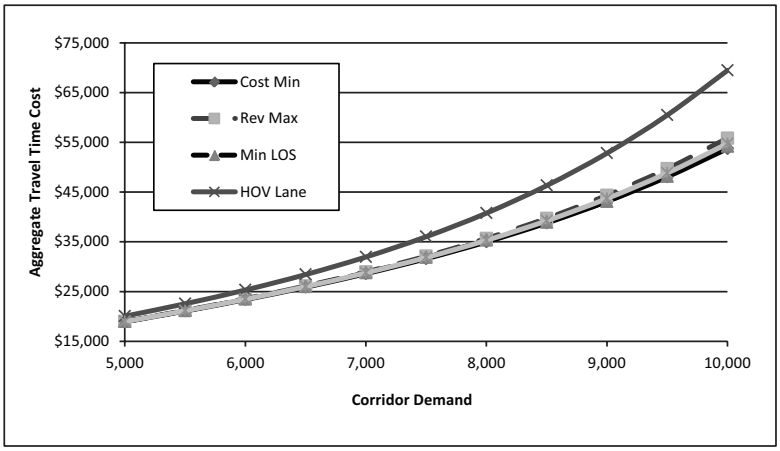


Figure 2: Relationship Between Toll Level and Aggregate Travel Time Cost, and Revenue Under Varying Corridor Demand and Tolling Objectives in Scenarios 1–3 (3 GP Lanes, 1 HOT Lane; HOVs Ride Free)

(1)



(2)



(3)

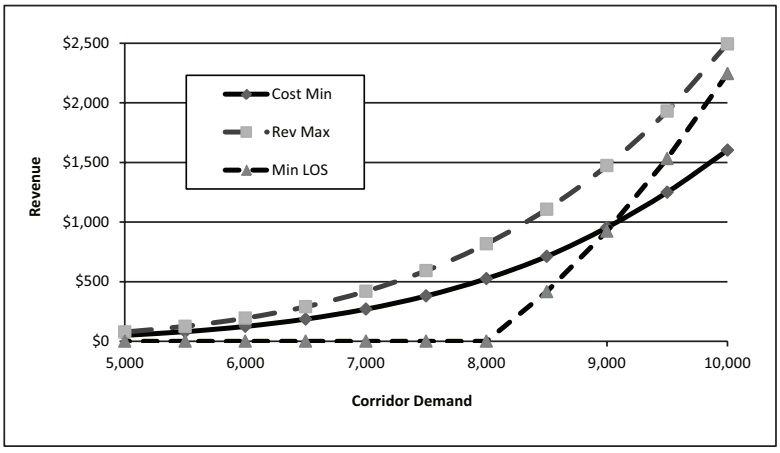
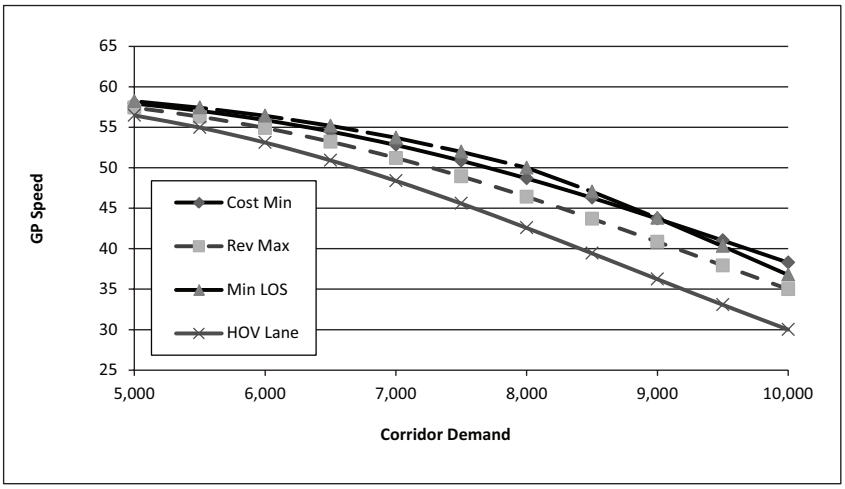
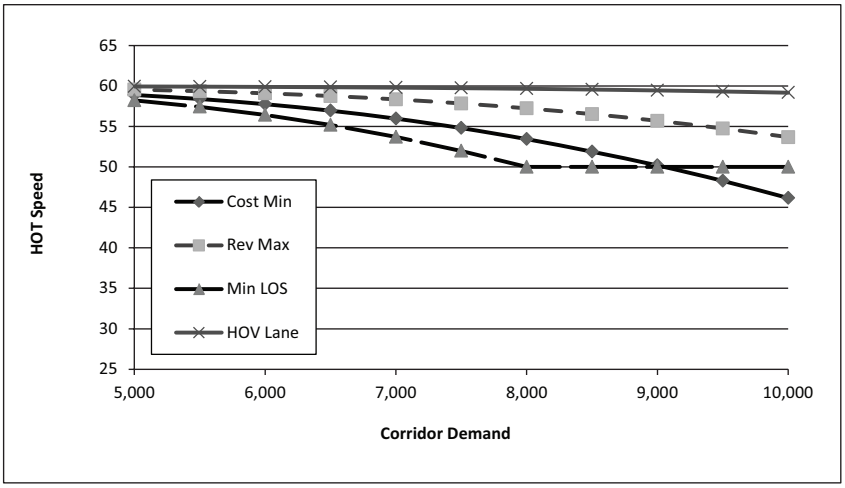


Figure 3: Relationship Between GP and HOT Lane Speed Under Varying Corridor Demand Tolling Objectives in Scenarios 1–3 (3 GP Lanes, 1 HOT Lane; HOVs Ride Free)

(1)



(2)



As shown in Figure 3, the HOV lane policy produces a slower speed in the GP lanes than the HOT lane policies. This is indicative of the fact that some SOV users purchase their way into the HOT lane under the HOT lane policy, but otherwise would have been forced to remain in the GP lanes under an HOV policy. In general, as the toll level in the HOT lane is lowered, more SOVs will purchase their way into the HOT lanes. This will improve the GP lane speed, but at the expense of potentially reducing the HOT lane speed.

Sensitivity of Results to a Higher Carpool Rate

The results presented above assume that approximately 10% of vehicles using the facility are carpool vehicles. In HOT lane evaluations, the share of carpool vehicles in the traffic stream will vary by location of the facility, direction, time of day, and day of week. In other analyses performed by the author using traffic count data for freeway facilities in the San Francisco Bay Area, the observed

share of vehicles using carpool lanes during the morning peak averaged around 10%, with higher levels observed during the afternoon peak period.

How do the results change as the share of carpool vehicles using the facility increase? Table 3 presents the results of a sensitivity analysis to identify the effect of increasing the share of carpool vehicles in the corridor to 15%, holding corridor traffic volume constant at 10,000 vehicles per hour (i.e. N = 10,000, N_S = 8,500, and N_C = 1,500). In this case, when carpools are allowed to use the HOT lane for free, the tolling authority effectively has less capacity to sell to SOVs. While there continues to be the potential for aggregate travel time cost reductions from converting the HOV lane to a HOT lane, these benefits are less than in the previous estimates where HOVs made up a small share of the traffic stream. For example, when the share of vehicles that are HOVs is approximately 10%, the change in aggregate travel time cost from going from an HOV policy to the HOT lane policy described by scenario one is $15,733 per hour (= $69,472 - $53,739, see Table 2). When the share of HOVs in the traffic stream is increased to 15%, the change in aggregate travel time cost generated by converting from an HOV policy to the HOT lane policy described by scenario one falls to $6,493 per hour (= $62,569 - $56,076, see Table 3). Revenue generating potential is also impaired as the share of vehicles that qualify as carpools (and can therefore ride free in the HOT lane) increases, making it less likely that the HOT lane will be financially self-supporting. For example, the revenue generated in scenario one falls by 32%, from $1,603 (in Table 2) to $1,087 (in Table 3) per hour, when the carpool share is increased from 10% to 15%. If, however, HOVs must pay to use the HOT lane, a higher share of HOV motorists using the facility can increase both aggregate travel-time cost reductions and the revenue potential of converting an HOV lane to a tolled lane. This can be seen by comparing the results for scenarios four through six in Tables 2 and 3 and stems from the fact that HOVs tend to have a higher value of time than SOVs.

Sensitivity of Results to Lower Carpool Values of Time

The final sensitivity analysis in Table 4 shows results when HOVs are assumed to have a lower mean value of time. By reducing the mean value of time associated with HOV users, the travel time benefits generated from providing faster travel to HOV users are given less weight in the aggregate travel time cost calculation. To illustrate the implications of this,, the mean HOV value of time is reduced from $40/hour to $30/hour in the results presented in Table 4, but all other assumptions about the vehicle population are held constant at their original values. When carpools are allowed to use the HOT lane for free, this change only impacts traffic volume, speed, the toll level, and revenue when tolls are set to minimize aggregate travel time costs. To illustrate this, consider the results for scenario one shown in Tables 2 and 4. Reducing the mean HOV value of time from $40/hour to $30/hour causes the toll level to fall from $1.35 (Table 2) to $1.17 (Table 4) for scenario one. As a result, more SOVs purchase their way into the HOT lane, and speed in the GP lanes improve slightly from 38.3 miles per hour (Table 2) to 38.6 miles per hour (Table 4). When HOVs must pay to use the HOT lane (scenarios four through six), the revenue generating potential of the facility is reduced as the mean HOV value of time is reduced. For example, the revenue generated under scenario 5 falls from $6,350 per hour (Table 2) to $5,946 per hour (Table 4).

CONCLUSION

HOT lanes have emerged as the most politically feasible form of congestion pricing in the United States. In the coming decade, it seems likely that more examples of the HOT lane concept will be put into practice. This paper has presented a simple HOT lane model that can be used for "sketch-planning" analysis to understand the likely performance of these facilities. Using a realistic numeric example, the model was used to gain insights into how HOT lane performance varies with the way in which facilities are designed and priced. The analysis suggests that different pricing objectives can

Table 3: Sensitivity Analysis with HOV Volume Increased to 1,500 Vehicles per Hour and SOV Volume Decreased to 8,500 Vehicles per Hour

	HOV Lane	All GP Lanes	HOT Lane(s)		
			Cost Min	Rev Max	Maintain LOS
			3 GP Lanes, 1 HOT Lane; HOVs Ride Free		
Scenario	*Base Case*		*(1')*	*(2')*	*(3')*
GP Volume (x_G)	8,500.0	10,000	7,785.1	8,018.4	8,000.0
HOV/HOT Volume (x_H)	1,500.0	NA	2,214.9	1,981.6	2,000.0
GP Speed (MPH)	33.2	40.3	38.3	36.6	36.8
HOV/HOT Speed (MPH)	56.4	NA	46.1	50.3	50.0
Marginal VoT ($\hat{v}$)	NA	NA	$34.30	$37.80	$37.46
Toll (*p*)	NA	NA	$1.52	$2.80	$2.70
Aggregate Travel Cost ($C(\hat{v})$)	$62,569	$57,081	$56,076	$56,721	$56,626
Toll Revenue ($R(\hat{v})$)	NA	NA	$1,087	$1,351	$1,349
			3 GP Lanes, 1 HOT Lane; HOVs Must Pay		
Scenario			*(4')*	*(5')*	*(6')*
GP Volume (x_G)			7,820.8	8,828.1	8,000.0
HOT Volume (x_H)			2,179.2	1,171.9	2,000.0
GP Speed (MPH)			38.0	31.0	36.8
HOT Speed (MPH)			46.8	58.6	50.0
Marginal VoT ($\hat{v}$)			$29.72	$37.68	$30.80
Toll (*p*)			$1.46	$5.74	$2.22
Aggregate Travel Cost ($C(\hat{v})$)			$55,792	$64,989	$56,133
Toll Revenue ($R(\hat{v})$)			$3,189	$6,726	$4,436
			2 GP Lanes, 2 HOT Lanes; HOVs Ride Free		
Scenario			*(7')*	*(8')*	*(9')*
GP Volume (x_G)			5,422.6	7,302.3	6,000.0
HOT Volume (x_H)			4,577.4	2,697.7	4,000.0
GP Speed (MPH)			35.8	18.6	29.8
HOT Speed (MPH)			44.7	57.6	50.0
Marginal VoT ($\hat{v}$)			$21.13	$29.74	$23.10
Toll (*p*)			$1.17	$10.81	$3.13
Aggregate Travel Cost ($C(\hat{v})$)			$55,715	$84,911	$58,143
Toll Revenue ($R(\hat{v})$)			$3,605	$12,943	$7,821

Notes: GP = general purpose; HOT = high occupancy toll; HOV = High occupancy vehicle; MPH = miles per hour; VoT = value of time; Cost Min = cost minimization; Rev Max = revenue maximization; Maintain LOS = maintain a minimum level of service.

Table 4: Sensitivity Analysis with Mean Carpool Value of Time Decreased to $30/hour

	HOV Lane	All GP Lanes	HOT Lane(s) Cost Min	HOT Lane(s) Rev Max	HOT Lane(s) Maintain LOS
			3 GP Lanes, 1 HOT Lane; HOVs Ride Free		
Scenario	*Base Case*		*(1'')*	*(2'')*	*(3'')*
GP Volume (x_G)	8,972.0	10,000	7,746.3	8,248.7	8,000.0
HOV/HOT Volume (x_H)	1,028.0	NA	2,253.7	1,751.3	2,000.0
GP Speed (MPH)	30.0	40.3	38.6	35.0	36.8
HOV/HOT Speed (MPH)	59.2	NA	45.4	53.7	50.0
Marginal VoT ($\hat{v}$)	NA	NA	$30.02	$34.67	$32.06
Toll (*p*)	NA	NA	$1.17	$3.45	$2.31
Aggregate Travel Cost ($C(\hat{v})$)	$65,940	$52,177	$51,493	$53,928	$52,146
Toll Revenue ($R(\hat{v})$)	NA	NA	$1,430	$2,495	$2,245
			3 GP Lanes, 1 HOT Lane; HOVs Must Pay		
Scenario			*(4'')*	*(5'')*	*(6'')*
GP Volume (x_G)			7,795.1	8,788.3	8,000.0
HOT Volume (x_H)			2,204.9	1,211.7	2,000.0
GP Speed (MPH)			38.2	31.2	36.8
HOT Speed (MPH)			46.3	58.4	50.0
Marginal VoT ($\hat{v}$)			$26.89	$32.95	$27.87
Toll (*p*)			$1.23	$4.91	$2.01
Aggregate Travel Cost ($C(\hat{v})$)			$51,190	$59,297	$51,593
Toll Revenue ($R(\hat{v})$)			$2,712	$5,946	$4,015
			2 GP Lanes, 2 HOT Lanes; HOVs Ride Free		
Scenario			*(7'')*	*(8'')*	*(9'')*
GP Volume (x_G)			5,375.8	7,676.2	6,000.0
HOT Volume (x_H)			4,624.2	2,323.8	4,000.0
GP Speed (MPH)			36.3	16.2	29.8
HOT Speed (MPH)			44.2	58.7	50.0
Marginal VoT ($\hat{v}$)			$20.14	$29.52	$21.98
Toll (*p*)			$0.99	$13.23	$2.98
Aggregate Travel Cost ($C(\hat{v})$)			$51,167	$94,013	$53,846
Toll Revenue ($R(\hat{v})$)			$3,564	$17,150	$8,848

Notes: GP = general purpose; HOT = high occupancy toll; HOV = High occupancy vehicle; MPH = miles per hour; VoT = value of time; Cost Min = cost minimization; Rev Max = revenue maximization; Maintain LOS = maintain a minimum level of service.

produce different results and that these differences in performance grow as there is more capacity available to sell. When comparing outcomes under different tolling objectives, the analysis suggests that the revenue maximizing toll level will be above the toll that minimizes aggregate travel time cost. When the toll is set to maintain a target level of service, it may be set above or below the toll, which will achieve other goals depending on the level of service target. General statements about the ability of HOT lanes to generate revenue or reduce aggregate travel time cost will depend critically on the characteristics of the facility, including how it is priced.

While the model presented here is capable of predicting outcomes under a broad range of policies with limited information, it has some shortcomings that should be highlighted and which represent areas for future extensions. First, the approach assumes a fixed number of motorists use the facility during the period under study. In reality, transportation policies such as HOT lanes can influence a variety of driving behaviors, which make this assumption questionable. In particular, motorists may vary when they make trips, where they are going, and whether trips are made alone, with others, via transit, or not at all.

One modification to the model that can potentially allow total demand to vary involves enabling motorists to choose between using the GP lanes, HOT lanes, or a third option, which represents not traveling on the facility during the period being modeled. In this case, the model must be calibrated to reproduce actual travel counts and a reasonable demand response to changes in the monetary and travel time cost of driving. A mode choice decision could also be integrated into the modeling framework, as is done in Yang and Huang (1999). This adds complexity to the model and the requirement for information on the mode choice decisions of corridor users, which may not be available. Finally, it may be possible to integrate a departure time choice into the modeling and spread traffic between different modeling periods, as in Arnott et al. (1993).

Acknowledgements

This paper has benefited from feedback from Martin Wachs, the editor Kofi Obeng, a reviewer, and seminar participants at the 52nd Annual Transportation Research Forum and RAND's Logistics Seminar Series.

Appendix

Derivation of Eq. (6)

The value of time $\hat{v}^*$ of the indifferent user which minimizes aggregate travel time cost will solve the first order condition $\partial C(\hat{v}^*)/\partial\hat{v}^* = 0$. This first order condition is,

$$\partial C(\hat{v}^*)/\partial\hat{v}^* = \frac{\partial t_G(x_G(\hat{v}^*))}{\partial x_G(\hat{v}^*)} \times N_S f(\hat{v}^*) \times x_G(\hat{v}^*) \times \frac{\int_{\underline{v}}^{\hat{v}^*} v dF_S(v)}{F_S(\hat{v}^*)} + t_G(N_S F_S(\hat{v}^*)) \times \hat{v}^* N_S f(\hat{v}^*)$$

$$\text{(A.1)} \qquad -\frac{\partial t_H(x_H(\hat{v}^*))}{\partial x_H(\hat{v}^*)} N_S f(\hat{v}^*) \times \left(N_S(1-F_S(\hat{v}^*)) \times \frac{\int_{\hat{v}^*}^{\overline{v}} v dF_S(v)}{1-F_S(\hat{v}^*)} + N_C \times \int_{\underline{v}}^{\overline{v}} v dF_C(v) \right)$$

$$-t_H(x_H(\hat{v}^*)) \times \hat{v}^* N_S f(\hat{v}^*) = 0.$$

Dividing through by $N_S f(\hat{v}^*)$ and rearranging the terms, Eq. (A.1) can be rewritten as,

$$\hat{v}^*\left[t_G(N_S F_S(\hat{v}^*)) - t_H(N_C + N_S(1-F_S(\hat{v}^*)))\right] =$$

$$\text{(A.2)} \qquad \frac{\partial t_H(x_H(\hat{v}^*))}{\partial x_H(\hat{v}^*)} \times \left(N_S(1-F_S(\hat{v}^*)) \times \frac{\int_{\hat{v}^*}^{\overline{v}} v dF_S(v)}{1-F_S(\hat{v}^*)} + N_C \times \int_{\underline{v}}^{\overline{v}} v dF_C(v) \right)$$

$$-\frac{\partial t_G(x_G(\hat{v}^*))}{\partial x_G(\hat{v}^*)} \times x_G(\hat{v}^*) \times \frac{\int_{\underline{v}}^{\hat{v}^*} v dF_S(v)}{F_S(\hat{v}^*)}.$$

From the equilibrium requirement in Eq. (2), the toll that can induce $\hat{v}^*$ is given by

$$\text{(A.3)} \qquad p^* = p^e(\hat{v}^*) = \hat{v}^*\left[t_G(N_S F_S(\hat{v}^*)) - t_H(N_C + N_S(1-F_S(\hat{v}^*)))\right].$$

Notice that both Eq. (A.2) and Eq. (A.3) equal $\hat{v}^*\left[t_G(N_S F_S(\hat{v}^*)) - t_H(N_C + N_S(1-F_S(\hat{v}^*)))\right]$. Thus, Eq. (A.2) and Eq. (A.3) are equivalent, implying that

$$p^* = p^e(\hat{v}^*) = \hat{v}^*\left[t_G(N_S F_S(\hat{v}^*)) - t_H(N_C + N_S(1-F_S(\hat{v}^*)))\right] =$$

$$\text{(A.4)} \qquad \frac{\partial t_H(x_H(\hat{v}^*))}{\partial x_H(\hat{v}^*)} \times \left(N_S(1-F_S(\hat{v}^*)) \times \frac{\int_{\hat{v}^*}^{\overline{v}} v dF_S(v^*)}{1-F_S(\hat{v}^*)} + N_C \times \int_{\underline{v}}^{\overline{v}} v dF_C(v) \right)$$

$$-\frac{\partial t_G(x_G(\hat{v}^*))}{\partial x_G(\hat{v}^*)} \times x_G(\hat{v}^*) \times \frac{\int_{\underline{v}}^{\hat{v}^*} v dF_S(v)}{F_S(\hat{v}^*)}.$$

Using the definition of $MEC_G(\hat{v})$ and $MEC_H(\hat{v})$ from Eq. (7) and (8) respectively, one arrives at Eq. (6), $p^* = MEC_H(\hat{v}^*) - MEC_G(\hat{v}^*)$. $MEC_G(\hat{v})$ and $MEC_H(\hat{v})$ represent the changes in aggregate travel time cost from a marginal increase in use in the GP and HOT lanes, respectively. For each vehicle class using either the GP or HOT lanes, it can be decomposed into the product of the change in travel time due to a marginal increase in use, the number of vehicles using the route, and the average value of time associated with those vehicles.

Derivation of Eq. (9)

The first order condition association with revenue maximization problem implies that the $\hat{v}^{**}$ that maximizes revenue satisfies the following first order condition

$$\text{(A.5)} \qquad \partial R(\hat{v}^{**})/\partial\hat{v}^{**} = -N_S f_S(\hat{v}^{**}) \times p^e(\hat{v}^{**}) + N_S(1-F_S(\hat{v}^{**}))\frac{\partial p^e(\hat{v}^{**})}{\partial\hat{v}^{**}} = 0.$$

From the equilibrium condition, Eq. (2), the toll that induces the revenue maximizing value of time of the indifferent user is given by $p^{**} = p^e(\hat{v}^{**})$. Thus,

$$\text{(A.6)} \qquad -N_S f_S(\hat{v}^{**}) \times p^{**} + N_S(1-F_S(\hat{v}^{**}))\frac{\partial p^e(\hat{v}^{**})}{\partial\hat{v}^{**}} = 0.$$

Next, adding $N_S f_S(\hat{v}^{**}) \times p^{**}$ to both sides of Eq. (A.6) and dividing both sides by $N_S f_S(\hat{v}^{**})$ reveals Eq. (9) $p^{**} = \dfrac{1-F_S(\hat{v}^{**})}{f_S(\hat{v}^{**})}\dfrac{\partial p^e(\hat{v}^{**})}{\partial\hat{v}^{**}}$.

Endnotes

1. Because aggregate social welfare is not something that can easily be measured, other HOT lane pricing objectives tied to observable metrics such as revenue generation or speed are likely to be given greater weight in practice.

2. Other HOT lane facilities are currently operating on I-10 and US-290 in Houston, Texas; I-25 and US-36 in Denver, Colorado; I-95 in Miami, Florida; and I-680 southbound in Alameda and Santa Clara County, California.

3. Revenues from the SR-91 Express Lane facility were even higher in previous years, reaching $50 million in 2007 (Orange County Transportation Authority 2007).

4. Carpool formation is not explicitly modeled here because it adds considerable complexity to the analysis. For an example of how one might model carpool formation in the context of tolled facilities that provide free access to carpools, see Yang and Huang (1999).

5. It is generally assumed in the congestion pricing literature that the toll revenue generated from congestion pricing will be returned to citizens through tax reductions or other means. As a result, the toll cost experienced by users is exactly offset by the redistribution of toll revenue back to citizens in welfare calculations. That is, the collection and redistribution of revenues effectively cancel each other out and are ignored in welfare calculations.

6. The distribution of the values of time for the SOV users that use the GP lanes reflects the left-hand side of the overall SOV value of time distribution, while the distribution of values of time for the SOV users that opt to buy into the HOT lanes represents the right-hand side of the overall SOV value of time distribution. For both groups of SOVs (i.e., those that travel in the GP lanes and those that travel in the HOT lanes), the respective value of time distributions represent a truncated distribution, with the truncation occurring on either the right or left of $\hat{v}$. The calculation of the mean value of time for each group reflects this truncation.

7. The derivation of Eq. (6) is in Light (2009) for the case where all vehicles, regardless of the number of occupants, must pay the toll to access a set of priced lanes that run parallel to a set of free GP lanes. Verhoef et al. (1996) derive a related expression for optimal toll on a priced route when there is a free alternative. In their analysis, demand is elastic but users are assumed not to vary in their value of time, and there is no distinction made between carpool and non-carpool vehicles.

References

Arnott, Richard, Andre de Palma, and Robin Lindsey. "A Structural Model of Peak-Period Congestion: A Traffic Bottleneck with Elastic Demand." *American Economic Review* 83 (1), (1993): 161-179.

Bureau of Public Roads. Traffic Assignment Manual. U.S. Dept. of Commerce. Washington, D.C., June 1964.

Cambridge Systematics. Twin Cities HOV Study: Volume 1. http://www.dot.state.mn.us/information/hov/pdfs/full_study.pdf, March 14, 2010.

Dahlgren, Joy. "High Occupancy Vehicle Lanes: Not Always More Effective Than General Purpose Lanes." *Transportation Research Part A: Policy and Practice* 32 (2), (1998): 99-114.

Federal Highway Administration. A Guide for HOT Lane Development. http://ntl.bts.gov/lib/jpodocs/repts_te/13668_files/images/13668.pdf, March 15, 2010

Federal Highway Administration. HOV/HOT Lanes. http://tmcpfs.ops.fhwa.dot.gov/meetings/uploaded_files/HOV%20HOT%20Lanes%20Brochure.pdf, March 15, 2010.

Hensher, David. "Influence of Vehicle Occupancy on the Valuation of Car Driver's Travel Time Savings: Identifying Important Behavior Segments." *Transportation Research Part A: Policy and Practice* 42 (1), (2008): 67-76.

Light, Thomas. "Optimal Highway Design and User Welfare Under Value Pricing." *Journal of Urban Economics* 66 (2), (2009): 116-24.

Liu, Louie and John F. McDonald. "Efficient Congestion Tolls in the Presence of Unpriced Congestion: A Peak and Off-Peak Simulation Model." *Journal of Urban Economics 44* (3), (1998): 352-66.

Metropolitan Transportation Commission. Bay Area High Occupancy Toll (HOT) Network Study December 2008 Update. http://www.mtc.ca.gov/planning/hov/12-08/HOT_Network_Report_12-08.pdf, March 18, 2010.

Orange County Transportation Authority. "91 Express Lane 2009 Annual Report." http://www.91expresslanes.com/generalinfo/91annualreport.pdf, April 5, 2010.

Orange County Transportation Commission. "91 Express Lane 2007 Annual Report." http://www.octa.net/91annual07b/test.pdf, April 7, 2010.

Poole Jr., Robert W. and Ted Balaker. "Virtual Exclusive Busways: Improving Urban Transit While Relieving Congestion." Policy Study No. 337 (Los Angeles: Reason Foundation, September 2005).

Safirova, Elena, Kenneth Gillingham, and Sebastien Houde. "Measuring Marginal Congestion Costs of Urban Transportation: Do Networks Matter?" *Transportation Research Part A: Policy and Practice* 41 (8), (2007): 734-749.

Small, Kenneth. *Urban Transportation Economics. Vol. 51 of Fundamentals of Pure and Applied Economics series*, Harwood Academic Publishers, 1992.

Small, Kenneth, Clifford Winston, and Jia Yan. "Differential Road Pricing, Express Lanes and Carpools: Exploiting Heterogeneous Preferences in Policy Design." *Brookings-Wharton Papers on Urban Affairs*, (2006): 53-96.

Small, Kenneth, Clifford Winston and Jia Yan. "Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability: Implications for Road Pricing." *Econometrica* 73 (4), (2005): 1367-1382.

Small, Kenneth and Jia Yan. "The Value of Value Pricing' of Roads: Second-Best Pricing and Product Differentiation." *Journal of Urban Economics* 49 (2), (2001): 310-336.

Sullivan, Edward and Mark Burris. "Benefit-Cost Analysis of Variable Pricing Projects: SR-91 Express Lanes." *Journal of Transportation Engineering 132 (*3), (2006): 191-198.

Turnball, Katherine. "HOV, HOT Congestion Pricing in the United States." *European Transport Conference Proceedings*, (1997): 97-104.

Verhoef, Erik, Peter Nijkamp, and Piet Rietveld. "Second-Best Congestion Pricing: The Case of an Untolled Alternative." *Journal of Urban Economics* 40 (3), (1996): 279-302.

Verhoef, Erik and Kenneth Small. "Product Differentiation on Roads: Constrained Congestion Pricing with Heterogeneous Users." *Journal of Transport Economics and Policy* 38 (1), (2004): 127-156.

Washington State Department of Transportation. SR 167 HOT Lanes Pilot Project First Annual Performance Summary: May 2008 – April 2009. http://www.wsdot.wa.gov/NR/rdonlyres/31FB3D24-79CC-4332-82F7-EBECEBE1CA71/0/HOTLanesAnnualReport2009.pdf, March 11, 2010.

Yang, Hai and Hai-Jun Huang. "Carpooling and Congestion Pricing in a Multilane Highway with High-Occupancy-Vehicles." *Transportation Research Part A: Policy and Practice* 33 (2), (1999): 139-155.

Thomas Light *is an economist at RAND and a professor of economics at the Pardee RAND Graduate School. His research focuses on public finance issues in the transportation and energy sectors. Prior to joining RAND, Light worked at ECONorthwest, where he was involved in over a dozen high occupancy toll lane feasibility studies. He holds a Ph.D. in economics from Cornell University.*

Microsimulating Automobile Markets: Evolution of Vehicle Holdings and Vehicle Pricing Dynamics

by Brent Selby and Kara M. Kockelman

Vehicle ownership decisions are central to estimates of emissions, gas tax revenues, energy security, pavement management, and other concerns. This work combines an auction-style microsimulation of vehicle prices and random-utility-maximizing choices, producing a market model for the evolution of new and used personal-vehicle fleets. All available vehicles compete directly, with demand, supply, and price signals endogenous to the model. The framework is described, analyzed, and implemented to show its capabilities in predicting outcomes of varying inputs. Application of the model system using Austin, Texas, survey data over a 20-year period highlight the model's flexibility and reasonable response to multiple inputs, as well as potential implementation issues.

INTRODUCTION

Automobiles dominate the U.S. transportation landscape. Much effort is put into the design of vehicles and the infrastructure they use, directly and peripherally. To understand and anticipate travel patterns, along with emissions, energy use, and gas tax revenues, transportation engineers and planners model vehicle ownership and use decisions. An appreciation of the near- and long-term effects of demographic, economic, and policy changes on vehicle fleet composition allows for more comprehensive planning. Many state, regional, and local transportation agencies must forecast the air quality, greenhouse gas contributions, and fuel tax implications of an evolving transportation landscape. This paper tackles the simulation of vehicle purchase and re-sale decisions via an auction process among individual households in the market for vehicles (new and used).

If a modeler can identify measurable attributes of consumers and producers that propel the buying, selling, scrappage, and use of cars and trucks, they can predict the choices made at an aggregate or disaggregate level using microsimulation. Several researchers have attempted to do this (e.g., Musti and Kockelman 2011, Mohammadian and Miller 2003, and Berkovec 1985) with varying complexity and scope. This work focuses on the choices made when households are offered the option to buy new or used personal vehicles, and the market clearing achieved by auction-driven price fluctuations. Previous works either overlook the used-vehicle market completely or depend on some function for price changes due to vehicle aging. This paper makes explicit the role of user preferences in vehicle price fluctuations through a market auction process, without strong assumptions about supply and demand. The model framework is applied with 5,000 U.S. households to illuminate inputs needed and predictive results.

LITERATURE REVIEW

A number of researchers have sought to model automobile markets. The frameworks depend on the analyst purpose as well as available data and computing power. At the core of most model specifications is a logit choice function to simulate consumer purchases. The transaction models can be summed up as follows: "From a utility-maximizing perspective, when the household's net utility gain from transacting exceeds a threshold, a transaction is triggered" (Mohammadian and Miller 2003, p. 99).

Earlier work by Berkovec (1985) allowed an oligopoly of manufacturers to sell to consumers and consumers to sell to each other or to scrappers. Notably, this included a random repair cost function and a market-clearing requirement in each period. Berkovec and Rust (1985) focused on each household's choice to keep or release a vehicle based on holding duration. These are much simpler than later models but laid useful groundwork, while identifying some important issues in model specification. Berkovec's (1985) model achieved market clearing conditions when the supply from manufacturers and current stock matched the demand by consumers and scrappers. To achieve this, he used a simple supply-demand function that adjusted price for each of 13 vehicle types, with demand summed over all consumers. This is the only model found that established market prices. He included devaluation in a vehicle's "expected capital cost," as a function of its current price and the previous model year's current price without consideration of usage or other heterogeneous trends. In Berkovec and Rust (1985), the depreciation is a simple constant (20% fixed, annual), regardless of year or vehicle type.

Musti and Kockelman (2011) and Mohammadian and Miller (2003) are the best examples of robust, recent models of the vehicle market. Musti and Kockelman (2011) simulated households in the Austin, Texas, region, with demographic and residential attributes evolving over time. There were many levels to their model, including population evolution, vehicle ownership, transaction decisions, and vehicle choice and use. The last sub-model also projected greenhouse gas emissions, but that was not part of the market portion of the simulation. Each year every household had to acquire a vehicle, retire a vehicle, or do nothing. The period ended when this was completed. No market clearing price mechanisms were simulated; exogenous prices were given based on current manufacturer suggested retail prices (MSRPs).

Their transaction model quantified the utility of vehicles owned by each household and available new from manufacturers. Vehicle choice relied on a multinomial logit (MNL) model using stated-preference survey results, neglecting past and current holdings. The households were heterogeneous in their attributes (socioeconomic and geographic) as well as their evolution. While their models simulated vehicle use (among the various fleet-evolution and market-focused models described here), they did not consider devaluation and maintenance at all. Conspicuously missing from their model was the buying and selling of *used* vehicles.

Mohammadian and Miller (2003) undertook a similar, MNL-driven simulation with fewer sub-models, but included an option to both release and acquire a vehicle. Used vehicles released by households in their model essentially vanished, and buyers could choose any model year they wanted, with prices given by exogenous market averages. To account for changes in utility as a result of evolving household attributes, the transaction model controlled for up/down changes in household size and number of workers (as opposed to these attributes' absolute numbers), but lacked home-neighborhood, age, and gender information. Mohammadian and Miller's (2003) choice model strongly depended on previous vehicle types and transaction decisions. Interestingly, they found that unobserved preference heterogeneity was not statistically significant after controlling for previous behaviors. This suggests that differences across decision makers may not be practically useful if information about their current and past vehicle holdings is known.

Mueller and de Haan (2009) constructed a bi-level choice model for new vehicles, randomly presenting consumers a subset of choice alternatives. Notably, it contained a Markov process to carry prior-owned-vehicle attributes (by household) over for new-vehicle choice. Esteban (2007) created a model to investigate the fleet effects of scrappage subsidies. She focused on transaction decisions and found that "a subsidy can induce scrappage even if it pays less for a used car than its without-subsidy price" (2007, p. 26). Since her work focused on national market dynamics, it provides little insight for household-level microsimulation. Emons and Sheldon (2002) gave a very different perspective in their implementation of a "lemons model," focusing only on vehicle attributes, rather than owner attributes. They predicted inspection failures, representative of car quality, based

on duration of ownership. No studies in the literature appear to integrate this information with microsimulation of consumer choices.

Berry et al. (1995) presented a method for combined empirical analysis of preference functions, cost functions, aggregate consumer attributes, and product characteristics to derive price estimates, quantities, profits, and consumer welfare. They found their model accurately reproduced actual US markets when changing one parameter at a time, ceteris paribus. Though they only used aggregate inputs and outputs, their approach could be used to feed information to a microsimulation model like those previously mentioned.

Auction Model Microsimulation

Though none of these market models used an auction method, such methods have advantages for pricing and vehicle selection. Products are auctioned, as suggested by Cassady (1967), if they have no standard value, such as antiques. Zhou and Kockelman (2011) used auctions to model real estate markets with various agents. If a property received no bids, the price fell by a certain (small) amount; with multiple bids, the price rose (by a similar amount). The bidding ended when each property hit its (pre-set) minimum price, received a single bid, or hit its (pre-set) maximum price (with a winning buyer randomly selected). Properties in high demand from buyers' experience price increases and those with little demand see prices fall. At or below a minimum threshold price, sellers can be assumed to keep their property. This may be described as a type of alternating double auction market. (See "Auctioning and Market Pricing" section of this paper and Sadrieh 1998, and Gibbons 1992 for more on these markets). Unlike Berkovec's (1985) approach, Zhou and Kockelman's (2011) auction did not require aggregate supply and demand equations.

Vehicle Depreciation, Lifespan, and Holding

Greenspan and Cohen (1999) described an upward trend in vehicle lifespan, with the median age of U.S. personal vehicles just 10 years for 1960 models, and nearly 13 years for 1980 models. DesRosiers (2008) describes heterogeneity in longevity (in Canada) with over 50% of large pickup trucks from 1989 still registered 19 years later, while only 8.2% of subcompacts remain. He shows that the median age for all vehicle types is at least 14 years, with most over 16 years. The 2001 (U.S.) National Household Travel Survey indicates that the average age of vehicles is 8.2 years. National Highway Traffic Safety Administration (Lu 2006) analysis showed that a typical passenger car would travel a lifetime mileage of 152,137 miles, while light trucks would travel 179,954 miles. In terms of holding durations, Emons and Sheldon (2002) found new U.S. vehicles to be held by a household an average period of four to six years.

Consumer Preferences and Decision Making

Three-quarters of respondents in Musti and Kockelman's (2011) survey placed fuel economy in their top three criteria for vehicle selection. However, fuel costs were not statistically significant in the corresponding revealed choice model. (This may be due to sudden changes in fuel price that happened after many of the owned vehicles were purchased.) While Espey and Nair (2005) found the opposite – that consumers did accurately value the savings from lower fuel cost. Bhat et al. (2008) suggested that people value fuel cost less than vehicle purchase cost, but with marginal statistical and practical significance.

Bhat et al. (2008) undertook one of the most comprehensive vehicle-preference studies based on travel surveys in the San Francisco region. They estimated how vehicle type, size, age, and use relate to each owner's socioeconomic attributes, as well as neighborhood attributes and the home's general location within the region. Specifically:

- Older people were more likely to have older vehicles, and younger people were more likely to have newer vehicles;
- Households with higher incomes and/or more workers tended to own fewer older vehicles and used less non-motorized transportation;
- Households in higher density, mixed use, and urban areas held fewer trucks and vans;
- Households in neighborhoods with bike lanes used more non-motorized transportation;
- Race and gender affect vehicle holdings and use; and
- In general, less expensive, bigger (by luggage and seating capacities), more powerful, and lower emission vehicles are preferred, ceteris paribus.

Mohammadian and Miller (2003) predicted the "do nothing" (neither buy nor sell) transaction status with much higher accuracy than any other choice. They found that buy and sell transaction choices were not influenced by the same variables. For example, an increase in the number of household workers seemed to induce a purchase or trade but not reduce the chance of a disposal. However, an increase or decrease in household size improved the chances of trading and disposing, respectively, while not affecting the chances of a purchase.

This work builds on these market and discrete choice concepts to provide a new method for simulation of an automobile market. It draws on several specifications from Musti and Kockelman (2011) fleet simulations, incorporating certain beneficial features of Storchmann's (2004) and Kooreman and Haan's (2006) work. It adds an auction strategy for pricing of used cars not yet available in the literature.

MODEL SPECIFICATION

The model used here includes two MNL models in sequence to predict each household's vehicle fleet from year to year. The first is a once-a-year market entrance model to simulate a household's decision to modify or maintain its "fleet" of personal vehicles. This choice model evaluates the probability that a household will choose to retire a vehicle, acquire a vehicle, or do nothing. The second MNL predicts which vehicle the purchasing/acquiring households will want, among available new and used vehicles. This vehicle choice model runs many times each year, within an auction model, to re-evaluate choices under different price conditions until equilibrium is reached. The objective of this work is to explore the features of such a framework, and examine the results of different context assumptions. The simulation described here was not calibrated as a whole, but rather constructed from previously calibrated models and empirical equations.

Market Entrance and Vehicle Choice Models

The utility model parameters for the market entrance model are based on those from Musti and Kockelman's (2011) transaction model, as given in Table 1. The choices are "acquire," "dispose," or "do nothing" (which serves as the base case). Since these are the only options in the data, a "trade" choice was not available, though it is highly desirable. Some parameter values required adjustment (as discussed in the Results and Conclusions section), since these choice models were calibrated in a different context.

Table 1: MNL Parameter Estimates for Annual Vehicle Transactions

Variable	Coefficient	T-Stat
Acquire (Buy)	-1.8314	-7.33
Dispose (Sell)	-3.7824	-8.96
Number of vehicles in the household x Dispose	0.4077	2.44
Number of workers in a house x Buy	0.2510	2.31
Female indicator x (Acquire, Dispose)	-0.3303	-1.79
Maximum age of vehicle in household x (Acquire, Dispose)	-0.0955	-4.63
Income of household x Do nothing	-2.25E-06	-1.33
Log Likelihood at Constants	-505.37	
Log Likelihood at Convergence	-448.65	
Pseudo R^2	0.3679	
Number of households	640	

(Source: Musti and Kockelman, 2011)

The MNL vehicle choice model estimates the systematic utility of each vehicle available in the market for each household. The model offers nine vehicle choices with distinct body types, fuel costs, and prices, representing the range of the most popular vehicles available in the U.S. Each of these nine vehicle types were offered as new (with set prices and unlimited supply) and competed with any used vehicle put up by sellers. Vehicle and household attributes serve as covariates in the utility expression (Table 2).

The first nine vehicle (and household) attributes shown in Table 2 are not specifically related to used vehicles and so were taken from Musti and Kockelman's (2011) vehicle choice model. In addition to these, four used-vehicle variables were added. Musti and Kockelman's (2011) model did not contain such variables, so these were derived based on other sources (Kooreman and Haan (2006) and Storcheman (2004), as discussed below.

The *Used* indicator x *Income class* level coefficient was approximated such that the lowest income groups are more likely and the highest income groups are very unlikely to choose a used car. The income groups were classified from 1 to 12 with 1 being the lowest (under $5,000) and 12 being the highest (above $250,000). At the lower income levels, this has a value in the utility equation close to the difference between two similar body types, making it slightly more probable that a buyer would switch from his/her optimal body type to a similar one if a reasonable used one is available. This was done on a purely intuitive basis, because such used-vehicle data do not exist. At high-income levels, a used car would decrease the utility at a value close to that expected between dissimilar body types, making a used car a very unlikely choice for a household making $200,000 or more each year.

The next two variables (*Price new x* 10^{-5} *x Used indicator* and *Price new x* 10^{-5} *x exp*(*age* ′ δ)) are based on the price when new and correspond to loss of vehicle value/utility with vehicle age. This is assumed to be universal to all buyers in the market. The values are based on Storcheman's (2004) price depreciation equation, as discussed later. Thus, the negative utility from vehicle aging should generally match the utility difference that comes with paying the initial auction price versus the new price. They will not exactly cancel, however, because different income groups are assumed to value used vehicles differently, and the market model allows prices to vary, as explained in the next section.

Table 2's last variable involves a 100,000-mile (odometer reading) indicator with current price to reflect the nonlinear drop in vehicle value associated with this significant usage milestone. The coefficient is such that the loss of utility will be that of 5% of its monetary value, as suggested by Kooreman and Haan (2006).

Table 2: Vehicle Choice Model Parameters

Variable	Coefficient	t-stat
Fuel cost	-8.514	-2.83
Purchase price (current) x 10^{-5}	-5.57	-3.94
Age of respondent less than 30 indicator x Midsize car	0.3627	2.28
HHsize greater than 4 indicator x SUV	0.8756	3.41
HHsize x Van	0.2895	4.66
Crossover sports utility vehicle (CUV*)	-0.4148	-2.43
Luxury car	-1.121	-3.51
Suburban x SUV	0.2632	1.32
Urban x Midsize car	0.1864	1.21
Used indicator x (Income class - 3)**	-0.3333	-
Price new x 10^{-5} x Used indicator**	5.57	-
Price new x 10^{-5} x exp(age ´ δ)**	-5.23	-
Over 100k miles indicator x Purchase price (current) x 10^{-5}*	-0.2785	-

Note: * CUVs are SUVs with a unit-body car platform. Popular models include the Honda CR-V and Toyota RAV-4.
** denotes variables added to the model of Musti and Kockelman (2009).

Auctioning and Market Pricing

In lieu of neglecting prices or referring to exogenous price functions, the model developed here uses an alternating double auction-based market pricing simulation, similar to that in Zhou and Kockelman (2011) and Sadrieh (1998) – and as described below, for prices of used vehicles (only). Unlike the transaction and vehicle choice models, the auction structure is not a direct simulation of the actions of buyers or sellers in the automobile market. Clearly, the sale of used vehicles directly or through dealers does not have such an open bidding process. Here, an auction bidding methodology is used to simulate prices, based on the preferences of individual buyers and offerings of actual sellers.

The market entrance model selects the (mutually exclusive) buyers and sellers participating in the market each year. The vehicles consist of new vehicles (in unlimited supply, with *fixed* prices) and those to be sold by households making a sell transaction. The buyers are the households making a buy transaction. The rules are such that all buyers must buy an automobile, and all used vehicles (from sellers) must be bought, returned to the selling household, or scrapped.

The alternating double auction is a discrete-time version of the standard ("open outcry") auction. It cycles or alternates between seller bids and buyer bids. Initially, sellers offer their vehicles at an opening bid set at prices (P_0), as described below. Buyers bid at that price on vehicles chosen by the vehicle choice model (i.e., those offering maximum net utility, after reflecting initial offer prices). Buyers act independently, and may only bid on a single (new or used) vehicle at each stage. There is no limit on the number of bids a vehicle can receive. At the beginning of the second cycle, sellers make price adjustments based on the buyers' bids. The sellers will decrease and increase prices of all used vehicles in zero- and two-plus (buyer-) bidder situations, respectively, by a small increment

(assumed to be 1% of the vehicle model's price new – or $200 for a $20,000 MSRP vehicle), while single-bid vehicles maintain their current price. The vehicle choice model then runs again, and all remaining buyers put in new bids on those vehicles offering them the greatest (random) utility gain. These cycles continue until all buy decisions have been executed.

If a vehicle's price falls below the scrappage price, it is immediately taken off the market and cannot return. If a vehicle's price reaches its maximum allowed price with more than one bidder, it is given, at that maximum price, to a randomly chosen bidder. A vehicle at maximum price is no longer evaluated by other bidders, but the winning bidder may choose to switch to a different vehicle as prices change. The minimum and maximum prices are set by an arbitrary $[P_0 - 0.15P_0, P_0 + 0.15P_0]$.

For the bidding to end, two conditions must be met: no vehicle may have more than one bidder and no vehicle may have zero bidders if it is at a price greater than its (exogenously set) minimum price. Similar to Zhou and Kockelman (2011), if a vehicle reaches its minimum price without bidders, it is returned to its owner.

The opening auction prices (P_0) of used vehicles are set using the logarithmic depreciation function recommended by Storchmann (2004), where $P_t = P_{new}\, e^{\alpha + dt}$. Here, P_t is price at year t, P_{new} is new price, and α and δ are depreciation parameters. There is also an additional 5% price drop for vehicles past 100,000 miles, as implied by Kooreman and Haan (2006), and the minimum P_0 is the scrappage price. Though Storchmann's (2004) study included regressions that were model- (and nation-) specific, a single number is used here for all models, for simplicity and because Storchmann (2004) did not include vehicles representing all body types. Only U.S. coefficient values are applied here, as shown in Table 3. Table 3's vehicle models were chosen by Kooreman and Haan because they are very common in the U.S. used-car market. In this study, these values were assumed to be α = -0.05 and δ = -0.175. It should be noted that the Civic and Accord are considered to have some of the lowest depreciation rates among all makes and models. (Lienert 2005, Consumer Reports 2010) Prices of new vehicles are set exogenously, based on MSRPs used in Musti and Kockelman (2011).

Table 3: Parameter Values for Price Depreciation from Storchmann (2004), $P_t = P_{new}\, e^{\alpha + dt}$

Vehicle Make & Model	α	δ
GM Cadillac Seville	-0.14	-0.163
Toyota Camry	-0.01	-0.168
Honda Accord	0.14	-0.191
Honda Civic	-0.15	-0.172

The Simulation Program

A simulation program was written in MATLAB's m-language, to mimic Austin households making new- and used-vehicle choices over 20 years. The program has a main layer that tracks households and vehicles over time, and a market–level layer that determines prices and vehicle selection in a given year, mimicking the layers of the logit models. The main layer tracks the state of households and vehicles and contains the "market entrance" functions. This includes selecting vehicles and buyers for the market, and updating ownership and other information. The market layer uses the vehicle choice model to determine purchases and runs until market clearance is achieved.

Figure 1: Schematic of the Simulation

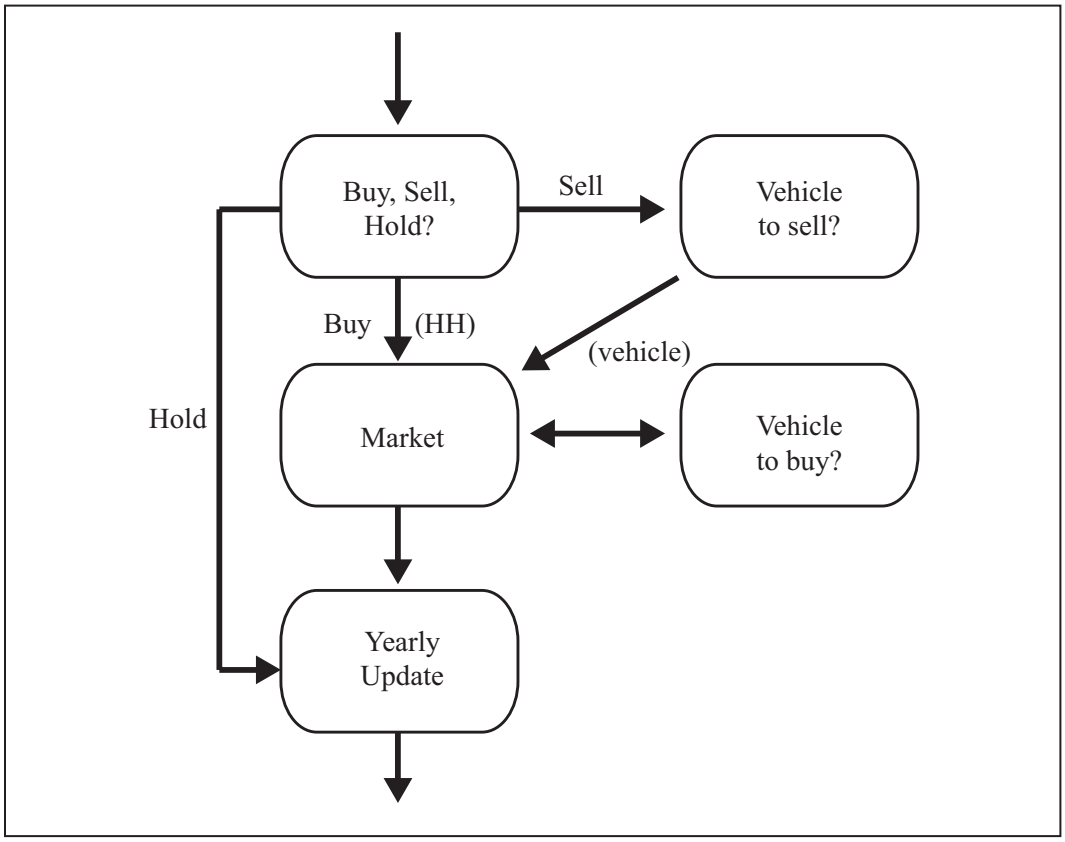


Figure 1 shows the basic flow in one year of the simulation. In the market entrance model, households choose to bypass the market (do nothing), sell a vehicle in the market, or enter it as a buyer. The vehicle choice model selects a vehicle in the household fleet to sell, and this vehicle is put into the market. In the market, vehicles and households are run through the vehicle choice model to determine which automobiles households wish to buy. After the market clears, the yearly update module places vehicles into their new (or old, if unsold) households and updates mileage and vehicle age information. The mileage added on a vehicle in any given year varies by its current owner, who has an associated usage per year, which is given in input data. The yearly mileages are based on averages from the household data and are held constant through the simulation.

The model was run for 20 year-long iterations on a fixed set of households. These households' attributes were not updated over time (to reflect aging individuals and the like), and no households are added or removed (to allow for more straightforward simulation). Such updating is, of course, feasible and useful in the context of real-world applications but beyond the focus of this work. The data used for simulation included 5,000 simulated households generated by duplicating the 637 households (not including those with incomplete data) from Musti and Kockelman's (2011) survey data. Use of 5,000 households allows for a market large enough to function but small enough to easily test. Table 4 provides a summary of these households' attributes (and the specific respondent on the Musti and Kockelman (2011) survey).

Table 4: Summary of Simulated Households' Attributes

	Average	Minimum	Maximum	Std. Dev.
Household Size	2.21	0	7	1.25
Number of Vehicles	1.61	0	5	0.87
Age of HH head (years)	36.8	20	70	15.0
Household Income ($/year)	86,271	5,000	250,000	67,048
Female Indicator	0.36	0	1	0.48
Number of Workers	1.46	0	5	0.85
Miles per Year per Vehicle	10,568	750	42,000	4,687

SIMULATION RESULTS

The simulation successfully ran through 20 years of market decisions among the 5,000 households in 25 to 40 minutes, with each year taking between 20 seconds and 10 minutes. The bidding loops generally took between 20 and 500 iterations, but occasionally required more than 1,000. This volatility can be greatly reduced by limiting repeated, similar-price steps, but was allowed here for simplicity.

Several tests were undertaken to examine the effects of changes in model parameters. One important adjustment was required in Musti and Kockelman's (2011) market entrance model: The value of the coefficient on maximum age of a vehicle in the household's fleet for the buy and sell options was negative (-0.0955), making it less likely that a household would get rid of a vehicle or buy a new one as its oldest vehicle aged. To address the issue of unreasonable holding durations and the resulting vehicle lifespans, a hazard function (for vehicle lifetimes) was added to randomly remove vehicles from households without selling them. This addition allows the model to account for irreparable, stolen, and destroyed vehicles (e.g., via collision or major mechanical failures), with the hazard (risk of vehicle loss) rising with vehicle age (i.e., probability=$1-ae^{b*age-c}$), based on NHTSA statistics (Lu 2006). While more detailed survey data may capture such effects, this exogenous function can fill in the gaps. Selby (2011) describes these changes and variations in user inputs in detail.

Table 5 compares the fleet mix in the high fuel-price and base fuel-price scenarios after 20 years of the simulation. The increased gas prices (at $5, rather than $2.50, per gallon) result in share reductions for large cars and all light trucks (CUVs, SUVs, pickups, and vans). Small share increases were observed in compact and midsize cars, with the majority of the shift going to the subcompact class, which offers the most fuel efficient vehicle type modeled.

Since governments sometimes choose to induce car turnover (thereby improving fleet emissions or safety) by offering scrappage subsidies (e.g., the Obama Administration's "Cash for Clunkers" program or those described in Esteban [2007]), such subsidies are an input parameter of interest. A simulation was done in which the scrappage incentive (per qualifying vehicle) was increased from $500 to $2,500 (for all vehicles). The new scenario encouraged an expected rise in vehicles sold for scrap and a drop in the numbers removed via the hazard function, as seen in Table 6. The average number of auction rounds fell by more than 50%, with vehicles exiting for scrappage more quickly. On average, only one vehicle went unsold every two auctions when the subsidy was offered. Additionally, used-car sales went down 12% (by about 475 vehicles), while new car sales were up 3% (by 225 vehicles). There were slightly more (1.5%) total vehicles (held initially plus purchased during simulation) with the higher scrappage rate offered, and somewhat fewer (-2.2%) purchases made. This may be the result of the removal of low-value cars that had been sold multiple times in the base case but scrapped early on in those with the higher subsidy. The distribution of vehicles' ages in the final simulation year (Year 20) did not change substantially between the cases.

Table 5: Model-Predicted Vehicle Holdings by Type After 20 Years

	Base Case Shares ($2.50/gallon) Year 20	**High-Fuel Cost Scenario Shares** ($5/gallon) Year 20
Subcompact	25.9%	35.0%
Compact	11.0%	11.8%
Midsize	14.6%	14.9%
Large	8.1%	6.8%
Luxury	1.1%	1.2%
CUV	7.0%	6.4%
SUV	6.5%	4.9%
Pickup	8.2%	5.8%
Van	17.4%	13.1%

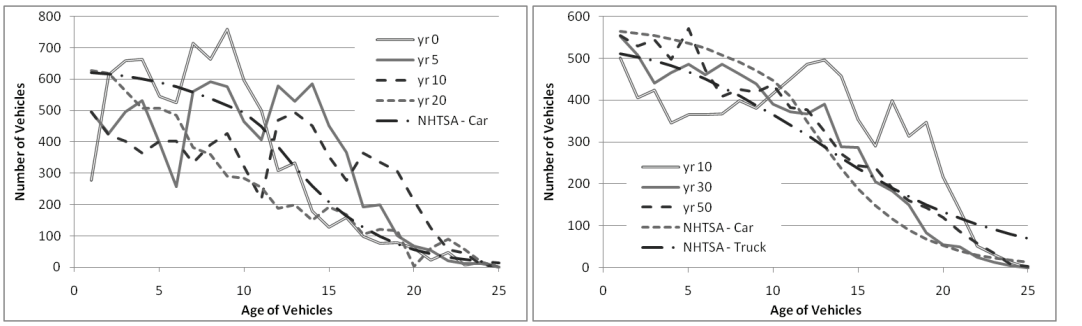
Table 6: Simulation Results for $500- and $2,500-per-Vehicle Scrappage Incentives

	Base Case ($500 Scrappage)		**Scrappage Subsidy** ($2500 Scrappage)	
	Per Year	**Total**	**Per Year**	**Total**
Buyers in Auction	557	11,146	545	10,897
Vehicles in Auction	201	4,023	203	4,053
Auction Rounds	346	6,914	154	3,081
Vehicles Unsold	2	47	1	10
Total Vehicles	15,294		15,517	
New Vehicles Purchased	7,255		7,478	
Used Vehicles Purchased	3,891		3,419	
Vehicles Scrapped	85		624	
Vehicles Removed by Hazard	8,250		7,808	
Average Vehicle Age in Year 20	7.81 yrs		7.95 yrs	

Figure 2 gives vehicle-age distributions at several time points over the simulation, for direct comparison with the NHTSA curves (Lu 2006) for cars and light trucks. It appears that, over the 20-year period, the program is reshaping the synthetic distribution of 5,000 households' vehicles into a smoother function. The rough peaks of the original data are removed by year 20, since those vehicles are all retired and have been replaced via a regular adoption of new vehicles.

Important concerns when running a simulation over a long period of time are the system's equilibrium, encroachment on boundary conditions, and/or cyclical patterns that the program may enter. Fifty-year runs were performed to examine the program's trajectory, and Figure 2 suggests that the model mimics the NHTSA curves (Lu 2006) rather well, which is heartening to see.

Figure 2: Vehicle-Age Distributions for 20-Year and 50-Year Simulations



Note: NHTSA Light Truck Curve Omitted for Readability of the 20-year Image

These various simulations illustrate the framework's flexibility, with results that highlight just a few of the comparisons that can be pursued. Not only can fuel, scrappage incentives, vehicle attributes, and household inputs be changed, but modules can be added without recalibration to incorporate more behavioral sophistication, including household evolution and greenhouse gas emissions estimation.

CONCLUSIONS

This work's results suggest significant potential of auction-style microsimulation for used- and new-car market modeling, while indicating areas for model enhancements. The general modeling approach offers analysts the advantage of determining market prices without requiring explicit supply and demand functions. It also sets all prices and purchase choices simultaneously, for the entire set of market actors (buyers and sellers). This type of model is designed to mimic disaggregate decisions on supply and demand, and microsimulation allows one to incorporate nearly limitless complexity in behavioral processes. With a fluid market and representative groups of buyers and vehicles, the prices and choices may tend toward an optimal set.

The approach taken here, to reflect transactions of used vehicles, extends the approaches taken in previous works – which either ignore such vehicles (e.g., Musti and Kockelman 2011) or assume an external supply of such vehicles (e.g., Mohammadian and Miller 2003). In this model, available used vehicles were compared directly to new vehicles by buyers. By comparing sale vehicle options directly, the model allows individual vehicles to have unique characteristics and avoids the assumption that every model year of a vehicle is for sale in a market. The auction structure sets prices based on the availability of vehicles and the individual preferences of people in the market. Prices and decisions thus react to market conditions such as changes in gas prices. With double gas prices, the model showed the subcompact's share jumping by 10% and the share of all truck types falling by 1% to 5%.

This simulation also suggests some opportunities for model enhancement. First and foremost, households should also be allowed to sell and buy vehicles in the same year – a feature not currently available due to lack of this choice in the survey from which the data is sourced. Consideration of budgetary constraints that many may be under when selecting a vehicle to pursue (and making an offer on that vehicle) would also improve its realism. The market entrance model populates the market with vehicles and buyers based on existing household and fleet attributes, while recognition of actual vehicle prices and availability in the new and used vehicle markets should prove more realistic. Robust data collection would encompass the current holdings and future plans of households, as well as the supply and pricing of vehicles. A shift in the conditions of the new and used markets will induce some to join and discourage others, changing market makeup.

The model used here also provides a history of prices, trades, and other information as outputs but does not use such information itself. A more sophisticated approach could incorporate it into subsequent years' market entrance decisions and pricing schemes. Previous information can provide a starting point for the current year. This would give some measure of continuity, a realistic assumption, from year to year. The effects of new vehicle price negotiation and credit availability may also be useful in future models. The framework presented here is quite flexible, and much can be added without substantive changes, including the evolution of households (e.g., the number, ages, and incomes of household members) and new vehicles (the fuel economy, price, and reliability).

As seen in the results, scrappage prices can affect market and vehicle holdings, with 3% more new cars sold and 12% fewer used vehicles purchased under a higher scrappage incentive. In addition to the price floor for scrappage, a hazard function was used to randomly remove vehicles as they age. This permits early and owner-unexpected exits/losses of vehicles due to a serious crash or other situations. Ideally, this loss should be better integrated with other market decisions (like vehicle use and age) or removed in favor of a more robust market calibration that more clearly models used-car behaviors. Predicting the price accurately depends somewhat on starting at the right point and a great deal on properly calibrating and quantifying the valuation of wear on a vehicle.

Including market pricing and used automobiles is a complicated but presumably central part of modeling a population's evolving vehicle fleet. This paper provides a framework for doing so and requires relatively few parameters for simulation. Additional work is necessary to add robustness and further empirical calibration of all model components.

Acknowledgements

We would like to thank Sashank Musti for sharing details of his past survey collection, Trevor Saas for helping generate synthetic-household data, Annette Perrone for her administrative assistance, and anonymous reviewers for their helpful comments.

References

Berkovec, J. "Forecasting Automobile Demand Using Disaggregate Choice Models." *Transportation Research B,* (1985): 315-329.

Berkovec, J. and J. Rust. "A Nested Logit Model of Automobile Holdings for One Vehicle Households." *Transportation Research B,* (1985): 275-285.

Berry, Steven, James Levinsohn, and Ariel Pakes. "Automobile Prices in Market Equilibrium." *Econometrica*, (1995): 841-890.

Bhat, C.R., S. Sen, and N. Eluru. "The Impact of Demographics, Built Environment Attributes, Vehicle Characteristics, and Gasoline Prices on Household Vehicle Holdings and Use." *Transportation Research Part B*, (2008): 1-18.

Cassady, R. *Auctions and Auctioneering*. University of California Press, Berkeley, 1967.

Consumer Reports. "10 Best and Worst Cars for Depreciation." *MSN Autos*, 2010. Accessed April 15, 2010, at http://editorial.autos.msn.com/article.aspx?cp-documentid=435652.

DesRosiers, D. "Observations: Trends in Longevity." DesRosier Automotive Consulting, 2008. Accessed from http://www.desrosiers.ca/2007%20Update/Documents%20and%20Reports/2008%20OBS/Obs%202008%20August.pdf on December 27, 2010.

Emons, W. and G. Sheldon. "The Market for Used Cars: A New Test of the Lemons Model." Centre for Economic Policy Research, 2002. CEPR Discussion Paper No. 3360. Available at http://www.vwl.unibe.ch/papers/dp/dp0202.pdf.

Espey, M. and S. Nair. "Automobile Fuel Economy: What is It Worth?" *Contemporary Economic Policy*, (2005): 317-323.

Esteban, Susanna. "Effective Scrappage Subsidies." *The BE Journal of Theoretical Economics*, (2007): 1-30.

Gibbons, R. *Game Theory for Applied Economists.* Princeton University Press, Princeton, New Jersey, 1992.

Greenspan, Alan and Darrel Cohen. "Motor Vehicle Stocks, Scrappage, and Sales." *The Review of Economics and Statistics,* (1999): 369-383.

Kooreman, Peter and Marco Haan. "Price Anomalies in the Used Car Market." *De Economist* 154, (2006): 41–62.

Lienert, Dan. "Ten Cars with the Best Residual Values." *Forbes.com,* 2005. Accessed April 15, 2010, http://www.forbes.com/2005/07/18/cars-vehicles-lifestyle-cx_dl_0718feat.html

Lu, S. "Vehicle Survivability and Travel Mileage Schedules." Washington: National Highway Traffic Safety Administration (NHTSA), 2006. DOT HS 809 952.

Mohammadian, A. and E. J. Miller. "Dynamic Modeling of Household Automobile Transactions." *Transportation Research Record* 1831, (2003): 98-105.

Mueller, M.G. and de Haan, P. "How Much do Incentives Affect Car Purchase? Agent-based Microsimulation of Consumer Choice of New Cars – Part I: Model Structure, Simulation of Bounded Rationality, and Model Validation." *Energy Policy* 37, (2009):1072-1082.

Musti, Sashank and Kara Kockelman. "Evolution of the Household Vehicle Fleet: Anticipating Fleet Composition, PHEV Adoption and GHG Emissions in Austin, Texas." *Transportation Research Part A*, (2011): 707-720.

National Household Travel Survey (NHTS). "National Data on the Travel Behavior of American Public," 2001. Accessed from http://nhts.ornl.gov/download.shtml on December 27, 2010.

Sadrieh, A. *The Alternating Double Auction Market.* Springer, Berlin, Germany, 1998.

Selby, B. "Spatial Prediction of AADT in Unmeasured Locations by Universal Kriging and Microsimulation of Vehicle Holdings and Car-Market Pricing Dynamics." Master's Thesis. Department of Civil Engineering, The University of Texas at Austin, 2011.

Storchmann, Karl. "On the Depreciation of Automobiles: An International Comparison." *Transportation,* (2004): 371-408.

Zhou, Brenda and Kara Kockelman. "Change in Land Use Through Microsimulation of Market Dynamics: Agent-based Model of Land Development and Locator Bidding in Austin, Texas." *Transportation Research Record* 2255, (2011): 125-136.

Brent Selby *is a travel demand modeler with Cambridge Systematics, Inc., based in Chicago, IL. He earned an MS degree from the transportation engineering department of the University of Texas at Austin under Professor Kara Kockelman and a BS degree in mechanical engineering from Carnegie Mellon University.*

Kara Kockelman *is a professor of civil, architectural and environmental engineering and William J. Murray Jr. Fellow at the University of Texas at Austin. A registered professional engineer, she holds a Ph.D., MS, and BS in civil engineering, a master's of city planning, and a minor in economics from the University of California at Berkeley. Dr. Kockelman's primary research interests include the statistical modeling of urban systems (including models of travel behavior, trade, and location choice), energy and climate issues (vis-à-vis transport and land use decisions), the economic impacts of transport policy, and crash occurrence and consequences. She teaches classes in transport economics, transport data acquisition and analysis, probability and statistics, and the design of ground-based transportation systems.*

A Comprehensive Rail Rate Index for Grain

by Adam Sparger and Marvin Prater

There are several annual rail rate indices commonly used to depict changes in the prices paid for rail service. While accurate for general analyses, each of these indices falls short in capturing the three major components of total railroad grain rates – tariff rates, fuel surcharges, and secondary railcar market costs. Grain is a rail commodity whereby bids in the secondary railcar market can affect whether the actual rate paid by shippers is above or below the published tariff rate. The seasonality of rates inherent in grain transportation is captured through the secondary market but is neither contained in other grain rail rate indices nor apparent in annualized data. In addition, most grain rate indices do not include fuel surcharges, which have become a major component of the total rate paid for any rail commodity movement. In this paper, we develop new rail rate indices for unit trains and shuttle trains and compare them against a rail cost index. The new indices are an improvement upon past grain rail rate indices by including information from the secondary rail market, fuel surcharges, and tariff rates into a weekly index between the years 1997 and 2011. The improved indices show a higher level of detail when compared to other annualized indices, allowing for a more thorough analysis of grain rates. These indices show grain rail rates generally higher than do other indices with a notable departure from rail costs at the beginning of the economic recession in 2009. A comparison of the rail indices with rail costs calls into question whether earlier conclusions about rail market power still hold.

INTRODUCTION

Rail rates have always been a contentious issue between railroads and shippers. On the one hand, rates must be sufficient to cover railroads' total costs, as well as provide an acceptable return on investment. However, rates should not be priced so high that the availability of railroad service becomes limited to only a handful of shippers, while forcing the rest to either adopt alternative transportation modes, if practical, or go out of business. As such, several recent studies have developed rail rate indices to analyze the changes in rail rates over time in order to evaluate the fairness and competitiveness of the railroad industry. While some of these studies have included a rail rate index for grain, none have been a comprehensive index from a shipper's point of view. This study creates a new comprehensive rail rate index for grain that includes the pricing components that are somewhat unique to grain movements: rail tariffs, fuel surcharges, and secondary railcar auction values.

Grain is an important railroad commodity. In 2010, grain represented 5.5% of all carloads originated, 8.2% of total tons, and 8.4% of total revenue for the Class I railroads (AAR 2010). In turn, railroads hauled 33% of all grain transported in the United States in 2007 (USDA/AMS 2011). The Surface Transportation Board (STB) notes that grain shippers have been concerned about rail rates over the past few years (STB 2009a). Some of their major concerns include greater reliance on shipper-owned rolling stock, pricing disincentives for single- and multi-car service, and lower rates for longer hauls. In addition, the Government Accountability Office (GAO) expressed its concern over competition and captivity in the rail industry (GAO 2006; GAO 2007). The STB and GAO developed rail rate indices for the rail industry overall, and the GAO developed a separate index for grain. Although their methodologies for creating rate indices differed, their findings were similar.

Overall rail rates generally declined between 1985 and 2004 before increasing in 2005, 2006, and 2007. The GAO's grain rate index, on the other hand, shows that grain rates have steadily increased between 1987 and 2005 and are 18% higher in 2005 than in 1985 in real terms.

Despite differences between methodologies, their main similarity is that the indices are from the railroad's perspective because they include only railroad revenues and exclude secondary railcar auction values. Grain is a unique rail commodity, whereby bids in the secondary rail market can affect whether the actual rate paid by shippers is above or below the published tariff rate. From the shipper perspective, secondary railcar values in addition to tariffs and fuel surcharges are all part of the total cost of shipping (Wilson and Dahl 2010, pg. 24).

In addition to secondary railcar auction values, fuel surcharges have become a major component of the total rate paid for any rail commodity movement over the past several years. For 2011, fuel surcharges on grain movements averaged 7% for unit trains and 10% for shuttle trains of the total cost paid to railroads (tariff rates plus fuel surcharges). While the STB index did include fuel surcharges, one reason that the GAO index may not have included this is due to inconsistent reporting methods by the railroads, as noted in the GAO report. Prior to the standardization of fuel surcharge reporting in 2009, some railroads reported fuel surcharges as miscellaneous revenue while others reported it as freight revenue between 2003 and 2008. The study on railroad competition by Laurits R. Christensen Associates, Inc. (2009, Vol. 2, pg. 8-10) further investigated the issues raised by the GAO and developed its own rate index for the time period of 1987 through 2006. The Christensen report developed two rate indices – one that included miscellaneous and fuel surcharges and one that did not. Both indices showed the same overall increase during this time period but with different patterns. The index with fuel surcharges was higher than the one without between 1992 and 1996, but lower between 1997 and 2006, with a considerable narrowing of their differences beginning in 2004. However, the Christensen report did not include a separate grain rate index with fuel surcharges.

OBJECTIVES

The objectives of this paper are twofold. The first objective is to develop comprehensive rail rate indices for grain in unit trains and shuttle trains utilizing all three major components of the total price. This involves combining weekly data from the secondary railcar market with monthly tariffs and fuel surcharges to create a weekly index between the years 1997 and 2011. The second objective is to compare the rail rate indices for grain with a rail cost index to measure how documented changes in the rail marketplace beginning around 2004 have specifically impacted grain rates.

These indices offer several benefits over previous grain rate indices. First, the level of detail shown at the weekly level is useful for studying the seasonality of total rail rates inherent in grain transportation, allowing for a more thorough analysis of grain rates than currently possible through the annualized indices of other studies. Second, these indices cover the most recent time period and are currently the only ones capable of providing analysis on rates through the economic recession beginning in December 2007. Third, they are the only indices which provide a comprehensive look at grain rail rates from a shipper's perspective to include secondary railcar auction results and fuel surcharges.

BACKGROUND

Rail service has evolved to be more responsive to market pressures through different mechanisms. The first mechanism relevant to the construction of the index is the development of unit trains and shuttle trains. Railroads began offering pricing incentives around the 1980s for larger car shipments from grain elevators to increase efficiency. Previously, cars were priced individually and assembled at a rail yard with cars from other origins to form a complete train. Unit trains are an innovation

over single-car pricing whereby cars are typically ordered in a block of 25-52 cars and receive a lower per-car price (Sarmiento and Wilson 2005). Shuttle trains are a further innovation whereby an entire train can be ordered, 75-120 cars depending on the railroad. This offers further efficiency gains over unit trains by avoiding the need to reassemble any single cars or blocks of cars at a rail yard in order to form a complete grain train. While there are differences among railroads about how many cars constitute a unit train or shuttle train, shuttle trains typically have several defining characteristics: the locomotives and crew are not detached from the grain cars and remain with them throughout the movement, the train service is contracted for a specified number of shipments over a six- to nine-month time period between specific origin-destination pairs, and there are loading and unloading time incentives (Sarmiento and Wilson 2005, pg. 1035). Thus, train sizes alone do not necessarily define the train type. Due to railroad differences in definitions, we have defined unit trains as between 25 and 75 cars and shuttle trains as 75 cars and greater for the purposes of this paper.

The second mechanism of interest is the creation of the primary and secondary railcar markets. Unlike barge, ocean, or truck rates, rail rates do not change on a weekly basis even if market pressures would demand otherwise. Railroads publish tariff rates that reflect the most likely market conditions to prevail given historical precedence and future expectations, while law requires them to give 20 days of notice before changing the published price. As such, rail rates are more insulated from weekly market changes and unexpected events, including weather, transportation disruptions, revised grain production or export sales data, and exchange rates. But as new information enters the market, pressures may distort the optimal supply and demand arrangement reflected by the tariff rates. This element of risk is captured through the primary and secondary railcar markets, which affect the overall price paid to transport grain.

Prior to the late 1980s, pricing for rail service was done through published tariffs that changed little throughout the year (Wilson and Dahl 2010, pg. 4). Thus, securing railcars was done on a first-come-first-served basis—meaning that during certain periods some shippers would not be able to secure rail service at any price, while others who had previously obtained service would not need it. Beginning with Certificates of Transportation in 1988, railroads began offering various forms of forward guaranteed railcar service in primary markets, which were tradable in secondary railcar markets (Wilson and Dahl 2010, pg. 4). As a vast improvement over the first-come-first-served allotments, the forward and transparent nature of secondary railcar markets makes them a risk mitigation method against changes in rail rates and as an assurance for railcar placement.

There are important differences between the primary and secondary railcar markets in their implications to constructing a rate index. Railroads auction an allotment of railcars for non-shuttle service (single car and unit train) and shuttle service in the primary market for placement during specific time periods. The winning bidders of these auctions can then re-auction these allotments in the secondary railcar market. Primary and secondary railcar auctions differ in that the revenue from primary auctions is paid to railroads. The revenue or shortfall in the secondary auctions, however, is income gained or lost for the bidder (elevator, grain trading firm, or other entity) that obtained the service in the primary market (Wilson and Dahl 2010, pg. 22). As the primary service holders, railroads have no incentive to accept a bid or provide an offer below their own published tariffs in primary auctions. Given their nature as instruments against risk, bids and offers can trade above or below published tariffs in secondary auction markets, resulting in revenues or shortfalls for the seller of the service contract in the secondary market. Railroads are not known to participate in the secondary market and conceivably would not have much incentive to participate. An exception might be if a railroad wished to reduce outstanding service obligations, for whatever reason, by purchasing back guaranteed car allotments.

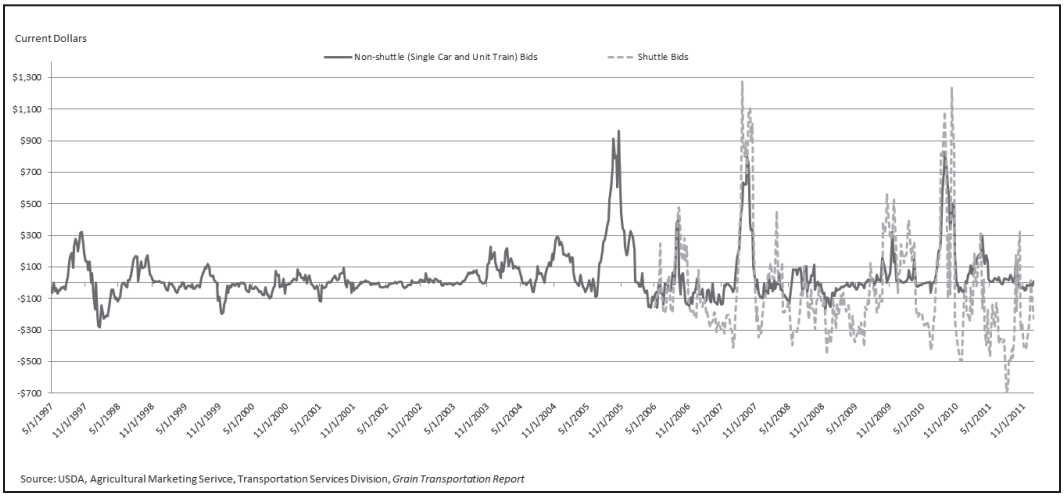
In times of ample railcar availability, shippers would not place a premium on risk reduction through guaranteed car allotments if service is readily attainable through regular tariffs alone. Thus, bidders who had previously acquired service allotments in the primary market would trade them

at a loss in the secondary railcar market if the bidder finds that service is unneeded. In times of high railcar demand and low railcar availability, the opposite scenario would occur and result in revenue gains. Wilson and Dahl (2010 pg. 22) found that between 2004 and 2010, more than 90% of primary auction results were at nil premium, meaning that shippers were able to obtain shuttle car commitments at tariff rates. They also found that the average secondary market value during the same time period was slightly greater than zero, meaning that trading guaranteed service allotments for risk mitigation in the secondary railcar market has proven desirable and profitable over time. Conversely, if the average secondary market value was consistently less than zero, shippers may forgo trading in the secondary market to avoid the associated monetary loss.

Data from the secondary railcar market are included in this rate index as opposed to data from the primary railcar markets for two reasons. The first is that a majority of primary auction results are at nil premium and, thus, do not add much additional insight into the actual cost of transporting grain than would the rail tariff alone. Since the primary market is constrained by zero at its lower bound, numbers alone make it difficult to distinguish a nil premium that represents a near perfect supply and demand equilibrium through published tariffs with a nil premium that represents an excess supply from tariffs priced above demand. Second, the results from the secondary market are a good depiction of the railcar supply and demand constraints for the grain industry. Supply and demand are tied to the agricultural production cycle, which necessarily affects the total cost of shipping at different points in the year. The results of auctions in the secondary railcar market are a better indicator of immediate grain rail service demands because service bought in the primary market may be re-traded in the secondary market as demand conditions change. The primary source of value in obtaining guaranteed railcar placement is to mitigate the risks associated with transport availability and cost (Wilson and Dahl 2005, pg. 8). The seasonality of agricultural shipments involves risk to the shipper, and mitigating that risk involves a premium that adds to the total cost. The seasonality is apparent in a graph of secondary railcar market results (Figure 1).

The data shown in Figure 1 are the weekly averages of the winning bids per car for the Burlington Northern Santa Fe Railway's (BNSF) and the Union Pacific Railroad's (UP) near-month non-shuttle (single car and unit train) and shuttle services trading in the secondary railcar market. Each secondary railcar market bid is relative to the regular tariff rate a shipper must pay with $0 representing bids trading at tariff. Thus, the bids represent either a premium or a discount to the regular tariff. For example, if a shipper purchases a guaranteed car allotment in the secondary railcar market with a winning bid of $100, then the shipper will pay an additional $100 per car above the published tariff rate to the seller, regardless of how much the seller previously paid for

Figure 1: Secondary Railcar Market Weekly Averaged Bids by Nearby Month



the guaranteed car allotment in either the primary or secondary market. Conversely, if the winning bid is -$100, then the purchaser will get a $100 per car discount on the published tariff rate via a loss to the seller. Typically, most of the values fall in the -$200 to $200 range. Although this range is relevant to the underlying tariff, which changes over time, bids within +/-$200, using absolute values, typically represent less than 3% of the value of the tariff rate across this time period. Bids between $200 and $300 are equivalent to a 12% increase, on average, to the tariff rate. However, during times of peak demand, bids can reach into the $600-$1000 range. Bids in this range are, on average, equivalent to a 31% increase in the published tariff rate. Bids reached a high during October 2005 in the $900s, representing a 47% increase to the published tariff rate. Values reach into the $600-$1000 range between August and October for three years: in 2005, after Hurricane Katrina severely disrupted major grain transportation arteries, in 2007, when record grain exports put high demand on available rail service, and in 2010, during the Russian export ban on grain. The Russian export ban on grain cut global supply and caused a global increase in demand for U.S. grain, leading to a premium on rail service by domestic grain shippers trying to meet demand. Despite atypical disruptions, the indicator is generally higher between August and October for any given year as shippers anticipate the fall grain harvest by bidding high premiums on service to ensure adequate rail capacity for their crop. In contrast, values below zero indicate bids trading below published tariff rates during times of weak demand. Typically, this has occurred between February and June, but as early as October in some years, such as the 2011/2012 marketing year, when less grain was transported after the harvest.

Also of note is the significant peak and trough beginning in August 1997 and ending in May 1998 that ranged between -$300 and $300. Following the Union Pacific and Southern Pacific merger, major transportation delays ensued across the western U.S. for grain and other shippers. During this period of widespread uncertainty, guaranteed car allotments traded at a premium in the secondary railcar market. The STB issued a joint petition for service order on October 31, 1997, which successfully addressed the problems and eventually returned traffic to normal. Following the STB's intervention, the premium on guaranteed car allotments began to fall and eventually traded at a discount for a short period of time.

METHODOLOGY

In order to create the rail index for grain rates, data from the STB's Confidential Carload Waybill Sample (STB 1997-2010) and the USDA's *Grain Transportation Report* (USDA/AMS 1997-2011) were used to construct a database including all three major components – rail tariffs, fuel surcharges, and secondary railcar market bid results. Like the STB rate index, controlling for changes in the commodity mix was a guiding component in order to avoid biasing the index. However, because this index is designed to provide an up-to-date snapshot of the current market for grain rail rates, all dollars for this index are current dollars. In our analysis, a specific inflation adjusted version of the index including only railroad revenues (tariffs and fuel surcharges) is compared against inflation related changes in railroad input costs. Dollars for the inflation-adjusted index were converted into 4th quarter 2011 dollars by the same method employed by the STB using the Implicit Price Deflators for Gross Domestic Product. The specific procedure is well documented in the Excel Workbook Documentation (STB 2009b) accompanying the STB's Rail Rate Study.

There are several important differences among the construction of this index, the STB index, the GAO index, and the Christensen index. First, both the STB and Christensen studies controlled for inflation in revenues, whereas the GAO study did not. Second, this index calculates the changes in per-car non-contract tariff rates to build upon the per-car non-contract tariff rate database in the USDA's *Grain Transportation Report*. In contrast, the other studies calculate the changes in revenue per ton-mile. Between 1997 and 2010, a majority of the sampled rates from the Waybill were non-contract for the selected routes except for 2003, 2007, 2009, and 2010. An advantage

of using only non-contract rates is their immediate availability for constructing an index. On the other hand, by excluding contract rates, the rail rate index may be higher than one utilizing contract rates under the assumption that contract rates are lower than non-contract rates. However, so long as the index is consistent in its rate composition over time, it should be a good indicator for relative price changes. Finally, this is an unweighted index designed to be timely and readily accessible for market purposes, putting it in contrast with the different weighting schemes used by the other indices.

Like the other studies, this index controls for changes in the commodity mix by classifying shipments into separate categories according to similar characteristics. The characteristics controlled for include shipment size (unit train or shuttle), origin-destination pairs, commodity, and rail carrier. Thus, changes in the per car tariff rates and fuel surcharges do not reflect changes in the composition of the underlying shipments but, rather, price changes imposed by the railroads on a consistent set of identical shipments over time. In contrast to weighting the price changes for each tariff and fuel surcharge, the indices developed here – one for unit trains and one for shuttle trains – are based on the unweighted changes in their respective monthly tariff rates and fuel surcharges.

The GAO study uses a fixed-weight method for controlling price changes in each shipment category. Their fixed-weight method uses relative shipment sizes from a base year to weight the relative contributions of each category. In contrast, the STB and Christensen studies use a chain-weighted Tornqvist Index (although they use different classifications for assigning changes to shipments). The Tornqvist method weights price changes in each category during each time period using the price ratio based upon the category's average contribution between two periods. For example, the price ratio at time n is calculated from the time n and time $n-1$ prices and weighted by their average contribution from time periods n and $n-1$. Each method, including the one presented below, has its advantages and drawbacks. In the academic literature, the chain-weight index is the preferred approach. However, our index is not necessarily meant for academic purposes, but rather as an industry tool containing up-to-date market data.

The USDA's *Grain Transportation Report* (GTR) provides a multifaceted analysis of the grain transportation industry, including important indicators and cost data. Since June 2010, the GTR has kept track of monthly rail tariffs for the most important grain corridors in terms of volume and geography. Unit train (between 25 and 75 cars) and shuttle (75 cars and greater) tariff rates per car are collected for wheat, corn, and soybeans moving in the larger and more predominant 286,000-pound grain cars between key origin-destination pairs. The GTR contains a monthly fuel surcharge database that can estimate the fuel surcharge for any grain movement by rail since 2000. In addition, the GTR includes a database of secondary railcar market auction bids covering non-shuttle service (including unit trains) since 1997 and shuttle train service since 2006.

Our comprehensive indices are based on the tariff rates and fuel surcharges for the representative grain corridors detailed above in the GTR. In addition, we combine the non-shuttle and shuttle secondary railcar market auction results from the GTR with the grain tariffs and fuel surcharges to approximate a shipper's total weekly cost for shipping grain by rail (Table 1). In order to build a historical database that would extend the tariff data within the GTR beyond June 2010, the Waybill samples were utilized to calculate monthly average tariff revenues between 1997 and May 2010 reported per car for unit trains and shuttles hauling corn, wheat, and soybeans consistent with the specific routes and rail carriers as published in the GTR. Thus, for 38 origin-destination pairs, there were approximate tariff rates per car using the Waybill between 1997 and May 2010 and actual tariff rates per car using GTR data between June 2010 and December 2011. These 38 origin-destination pairs include seven wheat, seven corn, and five soybean unit train routes and six wheat, seven corn, and six soybean shuttle routes. An unweighted average of the 19 unit train tariff rates with accompanying fuel surcharges was calculated for each month to derive a monthly series of the average per car rate. The same procedure was applied to the 19 shuttle rates and fuel surcharges.

Table 1: Data Sources for Components of Rail Rate Index

Component	Years	Source
Tariff Rates	01/1997 - 05/2010	STB Carload Waybill Sample
	06/2010 - 12/2011	USDA *Grain Transportation Report*
Fuel Surcharges	01/1997 - 12/2008	USDA *Grain Transportation Report*
	01/2009 - 05/2010	STB Carload Waybill Sample
	06/2010 - 12/2011	USDA *Grain Transportation Report*
Secondary Railcar Market Bids		
(Non-shuttle)	05/1997 - 12/2011	USDA *Grain Transportation Report*
(Shuttle)	05/2006 - 12/2011	USDA *Grain Transportation Report*

Because of inconsistencies in fuel surcharge reporting methods of railroads prior to the 2009 STB Waybill, the estimated fuel surcharges corresponding with each tariff were calculated from the GTR's fuel surcharge database for all years prior to 2009. Between 2009 and May 2010, fuel surcharges were obtained from the Waybill's fuel surcharge category. Actual fuel surcharges were used between June 2010 and December 2011, consistent with the actual reported tariff rates in the GTR (Table 1).

To derive the secondary railcar market data, the weekly winning bids for BNSF's and UP's near-month secondary railcar markets were averaged together. This was done separately for unit trains using non-shuttle bids and for shuttle trains using shuttle bids. The resulting weekly bids were added (or subtracted if the bids were below tariff) to the corresponding monthly average per car rate derived above. For example, the average per car rate including tariffs and fuel surcharges was $3,911 across the 19 unit train origin-destination pairs for December 2011. The average near-month secondary railcar market bids for non-shuttle trains for each week of December 2011 were -$16, $3, -$21, and $13, respectively. Thus, the average total costs to shippers for each week in December were $3,895, $3,914, $3,890, and $3,924, respectively. The total costs, including all three components were calculated for each week between May 1997 and December 2011 for unit trains and between May 2006 and December 2011 for shuttle trains. Due to the limitations of the GTR's secondary railcar market database, only the tariff rates and fuel surcharges are available for shuttle trains prior to May 2006, significantly shortening the span by which to create a comprehensive cost index for shuttle trains.

The base units for both indices are their first quarter averaged tariff rate with fuel surcharges from 2001. This time period was chosen as the base for the indices due to the limited availability of shuttle tariff data prior to then. An average of the first quarter was used instead of a single month in order to avoid any abnormal monthly variations and be as representative as possible. Weekly secondary railcar market data were excluded from the base of each index because it they were unavailable for shuttles, and we wanted both indices comparable over the same time frame by being consistent in the base value chosen.

Using an unweighted index may be misrepresentative under some circumstances. An unweighted index is equivalent to assigning equal weights to each of the underlying categories and is subject to some of the same criticisms of a fixed-weight index. If, in reality, one category contributes a smaller share to the index than another category, then an unweighted index would register changes in either category equally despite their proportional differences. Thus, the index could be misleading resulting from changes in the smaller, less representative category. However, given the nature and selection of the underlying categories chosen for this index, an unweighted

index is appropriate for the purposes of constructing an industry tool depicting changes in grain rail rates.

We compared two unit train indices – a chain-weighted Tornqvist Index that uses the number of carloads per month to weight changes in the total rate per car (tariffs, fuel surcharges, and secondary railcar market bids) with the unweighted index described above (Figure 2). Both indices covered the same time period, 1997-2010, based on the availability of Waybill data for reconstructing tariffs and constructing weights. They also used the same monthly tariff, monthly fuel surcharge, and weekly secondary railcar market data. The two indices move closely together, being within a 5% difference of one another for a majority of the time. The most divergence was just under a 14% difference for portions of 1999, 2000, and 2001, which was caused by especially heavy carload traffic on a couple of the corn routes. For the rest of the period, traffic volumes stayed relatively within the same bounds.

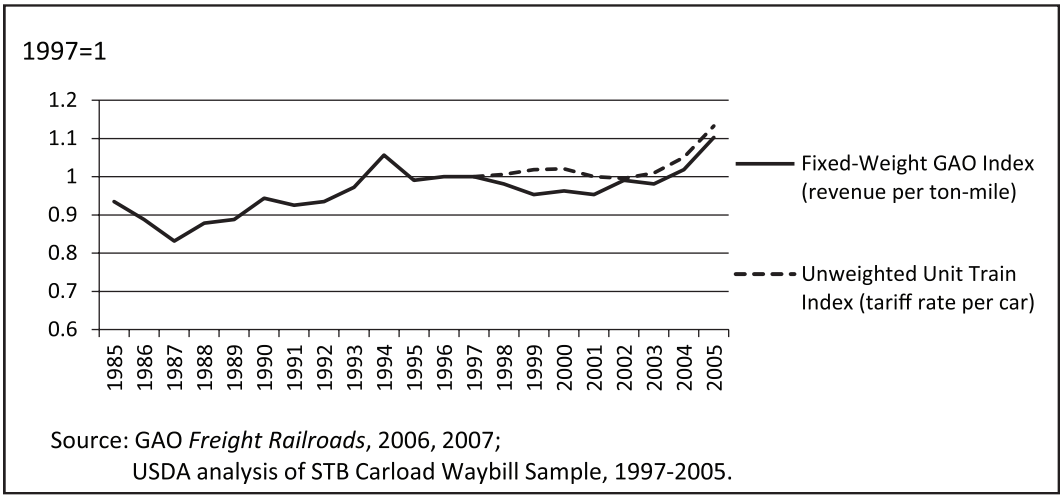
Figure 2: Difference Between Chain-weighted Tornqvist and Unweighted Index for Comprehensive Grain Rail Rates for Unit Trains

Furthermore, the underlying tariff data at the base of this index are a useful and representative approximation of changes in grain rates as compared to using revenue per ton-mile, as do the other indices. Figure 3 demonstrates the close comparison between the fixed-weight GAO grain index and the annualized tariff rate component of our unit train index (fuel surcharges and secondary railcar market results were excluded for consistency). A major advantage of this method is not having to rely on the Waybill for constructing weights and, thus, avoiding a one- to two-year lag on obtaining the most current data. This is also true for contract rates, which are contained in the Waybill. For further explanation, Christensen (2009) contains a detailed overview of the various methods and associated biases for each study.

RESULTS

Between May 1997 and December 2011, the unit train index stayed relatively flat until 2005, when it began generally trending upwards through 2011 with an overall low of 82 in January 1998 and an overall high of 230 in September 2010 (Figure 3). There were four discernible periods evident in the data: (1) May 1997 through March 2005, (2) April 2005 through March 2007, (3) April 2007 through December 2010, and (4) January through December 2011. The first period is characterized by a relatively flat trending rail index with a low standard deviation of 8.4, a maximum of 135, and a minimum of 82. The second period is marked by higher overall rail rates that have dramatic

Figure 3: Grain Rate Indices

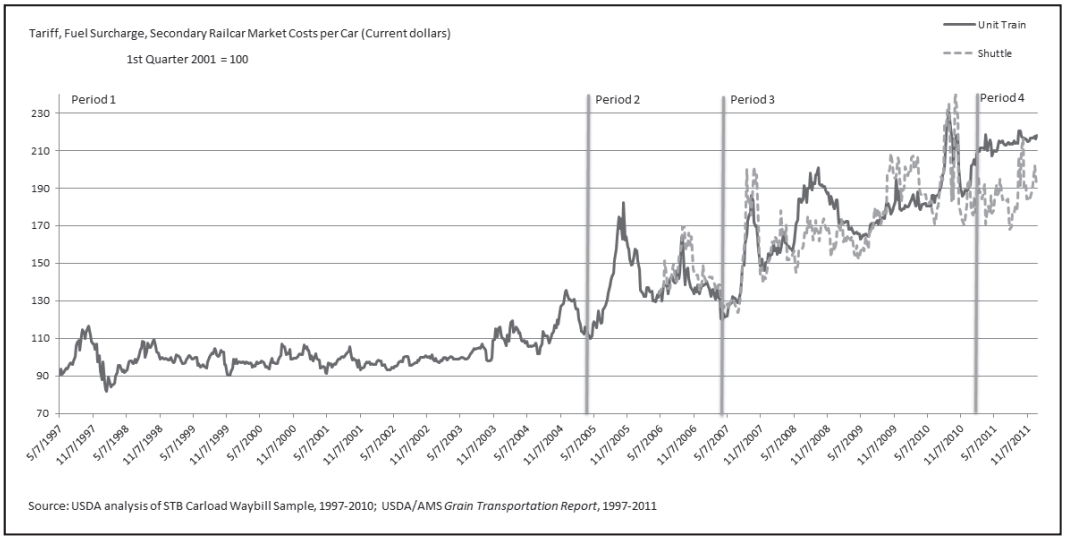


swings between highs and lows. The maximum and minimum are 182 and 110, respectively, and the standard deviation is 13.9. The third period shows a higher variance, standard deviation of 21.0, similar to the second period but with a constant upward trend, maximum of 230, and minimum of 120. The fourth period is most similar to the first period in terms of having a flat sideways trend, yet with the lowest standard deviation, 4.1, of any period. Its maximum and minimum are 221 and 202.

The shuttle and unit train indices move in tandem between May 2006 and December 2010 (Figure 4). However, beginning in the fourth period, a divergence begins to appear with the unit train index 27 points higher on average than the shuttle index throughout the period. The shuttle index, although shorter in length, can be separated into the same distinct time periods as the unit train. The shuttle index in the second period, beginning in May 2006, follows the same pattern as the corresponding unit train index. The standard deviation is 9.7, and the maximum and minimum are 169 and 134, respectively. The third period shows the same upward trend as the unit train index with a maximum of 244, minimum of 124, and standard deviation of 23.4. During the fourth period, the index trends sideways but with a higher volatility, with a standard deviation of 9.4 compared to 4.1 for unit trains. The maximum and minimum are 216 and 168, respectively. This divergence during the fourth period may show railroads' increasing preference for shuttles over unit trains, which is related to the issues raised by the STB (2009, pg. 7) stating shippers' worries of railroads attempting to "de-market" single-car and multi-car service to encourage shuttles.

As mentioned previously, these indices show the total costs for shipping grain from a shipper's perspective due to the fact that the shipper pays premiums in the secondary railcar market that the railroads do not receive. To examine the influence secondary railcar markets exert on overall rates, separate indices that excluded all secondary railcar market data were developed (Figures 5 and 6). Generally, the indices followed one another closely with a few dramatic exceptions where the secondary railcar market boosted overall rates above published tariff rates during times of increased risk for lack of car availability: August 2005 through January 2006 during the aftermath of Hurricane Katrina; August through October 2007 during a record U.S. export of corn, wheat, and soybeans; and July through October 2010 during the Russian grain export ban. The widespread service disruptions in the Western U.S. stemming from the Union Pacific and Southern Pacific merger also caused a notable deviation between secondary market and published tariff rates in 1997 and 1998 – initially the secondary market traded above tariff rates during the disruptions and then below tariff rates after STB intervention.

Figure 4: Comprehensive Grain Rail Rate Indices



Interestingly, the secondary railcar market had different effects on unit train and shuttle rates. For unit trains between May 1997 and December 2011, there was an almost even split between weeks in which the secondary railcar market caused the total cost of shipping to be greater (49%) and weeks in which it caused the total cost to be less (51%) than tariff rates and fuel surcharges alone (Figure 5). This finding is consistent when viewed between the narrower timeframe of May 2006 and December 2011 with the secondary market greater than tariff rates 48% of the time. In contrast, the secondary railcar market for shuttles caused the total cost to be greater than it otherwise would have been only 31% of the time between May 2006 and December 2011 (Figure 6). Shippers have more frequently placed a higher premium on mitigating risk through the secondary market for unit trains than for shuttles. This shows that obtaining adequate service for unit train shipments of grain has been harder than for shuttle trains during this time period.

Figure 5: Comparison of Unit Train Indices

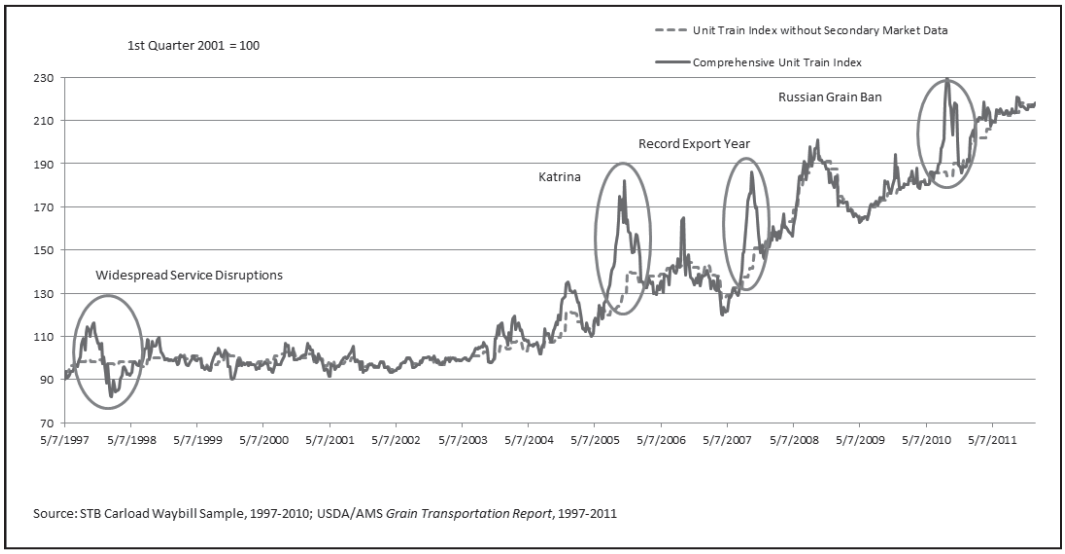
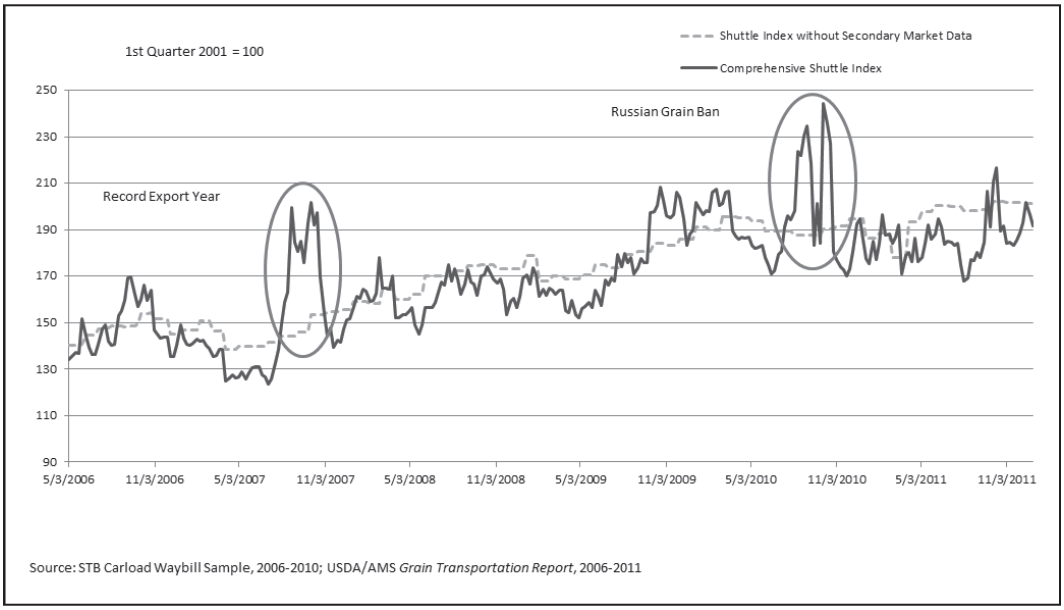


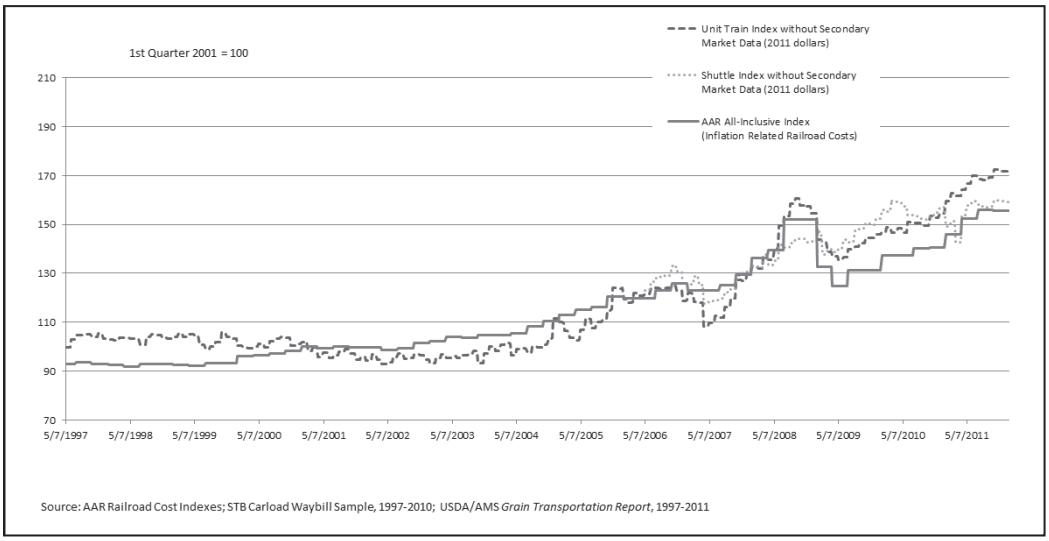
Figure 6: Comparison of Shuttle Indices



APPLICATION OF INDEX

A consistent finding among the rail rate studies has been that overall rail rates decreased between 1985 and 2000, had either zero or slight increases between 2000 and 2003, and increased noticeably from 2004 to the present. The evident rate increases beginning around 2004 have been the source of much controversy involving allegations of railroad market power and excessive profits after almost two decades of declining rates. Similar to the other studies, the rate indices presented here show that grain rates began increasing around 2004. Plotting the rate increases against railroad input costs becomes especially illuminating (Figure 7).

Figure 7: Real Grain Rates vs. Railroad Costs



The Association of American Railroads constructs the All-Inclusive Index, which measures changes in railroad inflation (AAR 2004; AAR 2011), on a quarterly basis. It is limited only to inflation-related changes in input price levels such as fuel, labor, materials, and supplies. When graphed against the inflation-adjusted rail price indices, we see that both prices and costs mirror one another until the beginning of 2009 during the economic recession. It appears as though rising rail rates beginning in 2004 are generally consistent with rising rail input costs. This is consistent with the finding of the Christensen study, which states that recent increases in rail revenue per ton-mile were the result of increasing input costs and not an exercise of market power between 1987 and 2008 (2009 Vol. 2, pg. 10-12). Nevertheless, the highest commodity markups are for grains, related to grain shipper captivity (2009 Vol. 2, pg. 11-30). The Christensen study (2009 Vol. 2, pg. 10-2) also notes that the rail industry cannot be classified as purely competitive or purely monopolistic, recognizing that some market power does exist while nevertheless being subject to some competition.

Beginning around January 2009, it appears that railroads were able to increase prices for unit train and shuttle service above market increases for railroad inputs. Rail rates for shuttle shipments experienced a dramatic increase, increasing over twice as fast as the rate of rail input cost inflation between February 2009 and December 2010 before leveling off to the input cost level. In comparison, rates for unit trains have risen faster and remained above railroad input costs throughout the period between January 2009 and the present. Especially during a time of recession, this raises questions of whether the Christensen study's findings still apply to the most recent data: (1) are increasing input costs, not railroad exercise of market power, still responsible for rate increases? and (2) does captivity relate to recent differences between unit train and shuttle prices? Still, a more detailed study would be necessary for investigating and interpreting these results beyond the preliminary trends presented here.

CONCLUSIONS

The comprehensive indices for unit train and shuttle grain rates developed here are a useful measure for capturing changes in the total cost of shipping from the shipper's perspective. The tariff rate and fuel surcharge components of the index are useful for tracking the longer run trends in grain rail rates, whereas secondary railcar market results reflect risk and the seasonality of grain shipping. The longer run trends show relatively sideways trending rail rates for unit trains until the beginning of an upward trend in 2004 with a rate increase of 95% between April 2005 and December 2011 in current dollars (67% adjusted for inflation). The shuttle index follows closely with the unit train index until September 2009 when it exhibits a less pronounced upward trend. Between May 2006 and December 2011, the shuttle index shows an almost 47% increase in current rail rates (29% adjusted for inflation).

Secondary railcar markets are useful for internalizing outside risk brought about by unexpected developments not otherwise captured in the stickier published tariffs. This ensures shippers have adequate service during times of increased uncertainty. The indices show this has happened in recent years during Hurricane Katrina, record grain exports in 2007, and the Russian ban on grain exports. However, the seasonality of grain shipments is also reflected in the secondary railcar market through normally higher premiums between August and October in anticipation of the annual grain harvest.

These two indices corroborate the findings of previous rate indices, which found the emergence of an upward trend in rail rates beginning in 2004. Based on these indices, it appears the increase in grain rates between 2004 and 2009 was related to the increase in railroad input costs. Only since the beginning of 2009 has there been a consistently visible difference between rail rates and railroad input costs. In contrast to unit train rates, the increase in shuttle rates during the recession appears to again be consistent with rail input costs. These findings raise the issues brought about by the STB

regarding shipper concerns over railroads "de-marketing" single-car and multi-car rates as well as Christensen (2009) regarding grain shipper captivity.

Despite any limitations in the construction of these indices, they should still prove useful to grain shippers who wish to track the seasonality and long-run trends of unit train and shuttle rates. They could also serve as a foundation for researchers who wish to expand upon these findings for academic purposes.

References

Association of American Railroads. *AAR Railroad Cost Indexes,* March 2004.

Association of American Railroads. *Freight Commodity Statistics,* 2010.

Association of American Railroads. *AAR Railroad Cost Indexes,* September 2011.

Government Accountability Office. *Freight Railroads: Industry Health Has Improved, but Concerns About Competition and Capacity Should Be Addressed*. GAO-07-94, 2006.

Government Accountability Office. *Freight Railroads: Updated Information on Rates and Other Industry Trends*. GAO-07-291R, 2007.

Laurits R. Christensen Associates, Inc. "A Study of Competition in the U.S. Freight Railroad Industry and Analysis of Proposals That Might Enhance Competition." Report prepared for the Surface Transportation Board. Madison, WI, 2009.

Sarmiento, Camilo and William W. Wilson. "Spatial Modeling in Technology Adoption Decisions: the Case of Shuttle Train Elevators." *American Journal of Agricultural Economics* 87(4), (2005).

Surface Transportation Board. *Confidential Waybill Sample,* 1997-2010.

Surface Transportation Board. *Study of Railroad Rates: 1985-2007,* 2009a.

Surface Transportation Board. *Excel Workbook Documentation: For Computations Made in the STB Rail Rate Study,* 2009b.

U. S. Department of Agriculture, Agricultural Marketing Service. *Grain Transportation Report,* 1997-2011. Accessed January 13, 2012. http://www.ams.usda.gov/AMSv1.0/gtrdata.

U. S. Department of Agriculture, Agricultural Marketing Service. *Transportation of U. S. Grains: A Modal Share Analysis, 1978-2007,* 2011.

Wilson, William W. and Bruce L. Dahl. "Railcar Auctions for Grain Shipments: A Strategic Analysis." *Journal of Agricultural & Food Industrial Organization* 3(2), (2005): Article 3.

Wilson, William W. and Bruce L. Dahl. "Grain Pricing and Transportation: Dynamics and Changes in Markets." Agribusines and Applied Economics Report 674. Fargo: North Dakota State University, Department of Agribusiness and Applied Economics, 2010.

Adam Sparger *is an economist with the Transportation Services Division, Agriculture Marketing Service, U.S. Department of Agriculture. Adam works in different areas related to transportation and agriculture but specializes in one of his main interests and fascinations – railroads. Adam received a B.A. in economics from the College of William and Mary and an M.S. in Agricultural Economics from Virginia Tech. He has published articles on different aspects of agricultural economics through academic journals and the Department of Agriculture. He became a member of the Transportation Research Forum in 2012.*

Marvin Prater *is a transportation economist specializing in railroad transportation and rural infrastructure issues and is employed by the Transportation Services Division, Agricultural Marketing Service, U.S. Department of Agriculture. Marvin earned a B.S. in horticulture, a Master's in business administration, and a Ph.D. in economics from Kansas State University. Marvin has been a member of the Transportation Research Forum since 1997, presented papers at the annual forum, and authored papers for the* Journal of the Transportation Research Forum *and the U.S. Department of Agriculture.*

Evaluating the Efficacy of Shared-use Vehicles for Reducing Greenhouse Gas Emissions: A U.S. Case Study of Grocery Delivery

by Erica Wygonik and Anne Goodchild

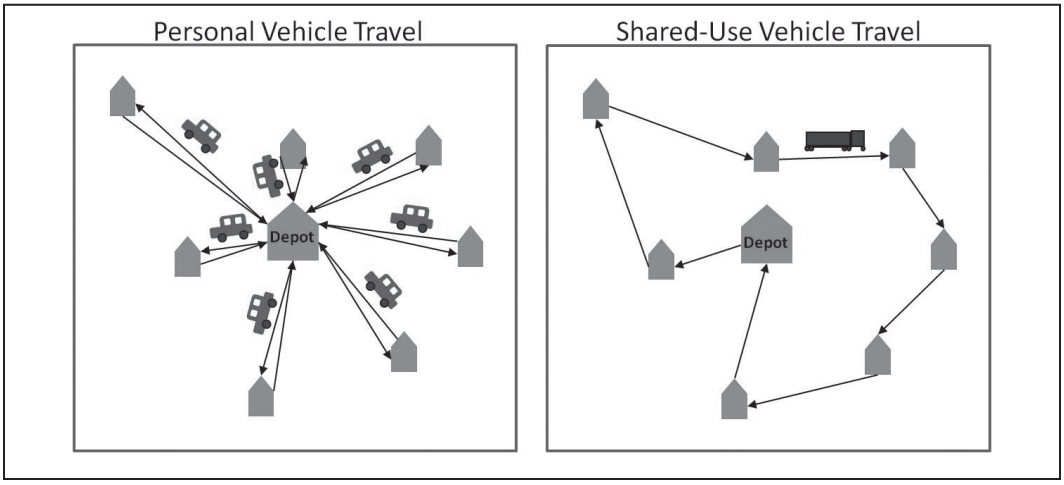
This paper compares the CO_2 emissions from the use of personal vehicles to shared-use vehicles for grocery shopping in Seattle, Washington. The research builds on existing literature by considering the importance of modeling the logistical details of routing and scheduling, and by comparing the results of an American case study to existing European case studies. We find the US and European case studies to provide consistent results, that low customer density provides greater opportunities for emissions reductions, and that logistical efficiencies can account for approximately 50% of CO_2 reductions.

INTRODUCTION

Under agreement of the Kyoto Protocol (United Nations 1998), governments worldwide are attempting to reduce greenhouse gas emissions. Efforts to address this concern are generally siloed – focusing on addressing the impacts of a particular contributing activity (*A Wedge Analysis of the U.S. Transportation Sector* (Simon et al. 2007) is one example which allocates necessary reductions to flatten emissions to each transportation source). This paper examines one way to consider the overall impact of transportation by relating freight activity and passenger travel. Further, the delivery services evaluated are immediately implementable and, thus, can begin addressing environmental concerns quickly.

Shared-use vehicle transportation services provide for the movement of passengers and goods and may offer opportunities for reducing the environmental footprint of these activities when compared to individuals using personal vehicles (Figure 1). For example, some large employers have developed their own shared-ride services and many municipalities provide both garbage and school bus services.

Figure 1: Illustration of Personal Vehicle Travel Compared to Shared-Use Vehicle Travel



These services reduce individual employee trips to the workplace, household trips to the transfer station, and household trips to schools by collecting passengers and goods into one vehicle and reducing vehicle miles travelled (VMT) (Cairns 2005). While the literature shows these services require fewer vehicle miles of travel, the vehicles they rely on have greater emissions of greenhouse gasses per mile. Thus, the net results from these services are unclear – does the more efficient routing outweigh the impacts from the higher-emission producing vehicles?

Research into the benefits of shared-use vehicles has generally focused on VMT but has not sufficiently considered the influence of spatio-temporal customer density, routing, and scheduling on the outcomes. Some services, like waste collection, third-party logistics, and school buses, dictate when customers are served and are able to serve proximate customers with the same vehicle, reducing VMT per customer. Other services, including many commercial services such as appliance, furniture, and grocery delivery, are dedicated to customer service or have low customer density, and they must create truck routes based on customer demands, which require serving a more spatially-random set of households. These services would typically have a higher VMT per customer. This paper investigates the potential CO_2 emissions savings for these two bounding cases – when customers are selected randomly or are assigned by location. This provides insight into the magnitude of the effect of logistical decisions on the emissions from a shared-use vehicle service, and under what circumstances these services can provide most benefit over individual-use vehicles. The results of this work will identify a potential method of reducing greenhouse gas emissions and will inform the practicality of addressing such questions as "How can the use of these services be encouraged?"

Much of the research comparing personal vehicle travel to shared-use vehicles has been completed in Europe. While Europe is comparable to the United States in many regards including relative economic strength and development, in general, Europe has higher levels of population density and differing transportation patterns. Newman and Kenworthy (1999) compare data from selected cities in Europe and the United States and illustrate U.S. cities on average use 2.5 times more energy for transportation per capita than European cities on average. European metropolitan areas have 3.5 more people per hectare and 3.8 more jobs per hectare than American ones on average. There may be other relevant differences between American and European cities, including roadway design. Given these differences, the research in Europe may not translate to American cities.

The research described in this paper uses grocery store shopping in Seattle, Washington, as a case study to quantify and compare the CO_2 emissions due to personal versus shared-use travel. Grocery shopping is a regular activity for most households, and is highly regional (most shoppers visit a proximate store). Due to its regularity, grocery shopping has potentially greater environmental impacts than more sporadic shopping trips (e.g., for electronics). Additionally, most grocery shopping is currently done in a traditional retail environment, in which consumers drive personal vehicles to and from supermarkets. While separate fields examine the behavioral issues associated with delivery services (see Tanskanen et al. 2002, for one example) and the financial viability of these types of services (Punakivi et al. 2001, is an example), this research complements that work by focusing on operational impacts and does not consider the financial viability, adoption levels, or willingness to pay considerations. The analysis indicates whether shared-use vehicles can show significant benefit to the environment over personal vehicles, if results from a United States' city are consistent with findings from Europe, and the extent to which logistical details influence the magnitude of benefit.

LITERATURE REVIEW

Evaluations of Environmental Impact of Shared-Use Vehicles

Few researchers have compared the environmental impact of replacing passenger travel with freight travel. Stefan et al. (2005), Hunt and Stefan (2007), Quak and de Koster (2007, 2009), Palmer (2007), Wygonik and Goodchild (2011), and Gebresenbet et al. (2011) have examined environmental impacts of urban commercial vehicles but not in contrast to personal vehicle use. Dessouky et al. (2003) consider trade-offs between cost, service, and environmental performance for a demand-responsive transit operation, but also do not compare these gains to the environmental impact of the personal vehicle trips the transit service might replace.

The American Public Transportation Association Transit Fact Book (2010) and Shapiro, et al. (2002) look at emissions per passenger mile for different vehicle types, using fleet averages, to show the benefits of public transit. Barth et al. (1996) examined the emissions implications of replacing personal travel with public rail service, finding rail produced fewer of certain emissions and personal travel produced fewer of others, but they did not examine CO_2 emissions, and their calculations relied on approximated average trip length and speed information. Delucchi et al. (2002) examined a number of cases for a handful of U.S. cities comparing personal travel to various forms of transit, finding transit generally produced fewer emissions, but factors including occupancy, electricity source, and access mode can significantly alter the results. Vincent and Jarram (2006) completed a strategic analysis using average travel patterns and emission factors to compare the CO_2 emissions associated with passenger travel, light rail transit, and bus rapid transit (BRT), finding both light rail and BRT systems would have significant reductions in CO_2 emissions over passenger travel, with the BRT reductions more than double the light rail reductions.

For cases where delivery vehicles replace personal travel, Matthews et al. (2001) compare the environmental impacts of traditional retail storefronts and e-commerce sales of books. Their analysis provides sketch-level bounds on the two cases and includes returning unsold books, personal travel, freight travel, production, and packaging impacts. Their results show e-commerce has lower environmental impacts between their two studied cases, but changing the parameters of each case will yield different outcomes. For example, while their evaluation conservatively assumes all e-commerce books travel via air for a portion of their trip, if the distance traveled by air increases by less than 10% the two sales methods have comparable environmental impacts. Kim et al. (2008) compare traditional shopping, e-commerce, and delivery to centralized drop-off locations, finding both e-commerce and delivering to centralized locations have significantly lower CO_2 emissions. McKinnon and Edwards (2009) compared shopping trips with home delivery of small, non-food items and found delivery services almost always result in fewer grams of CO_2 emissions, even when accounting for additional trips demanded from returns and redelivery needs, and adjusting consumer trip impacts to account for bus use and trip chaining. McKinnon and Woodburn (1994) suggest the CO_2 emissions associated with the final transport from the grocery store to homes via personal automobiles are significantly greater than the CO_2 emissions with the earlier steps in the supply chain. Edwards, et al. (2010) reconfirmed that for non-food items, delivery services have fewer CO_2 emissions than personal travel unless very large numbers of goods are purchased in trips made by personal vehicle.

The literature indicates a potential for CO_2 emissions reductions associated with certain mode shifts, but few papers have examined replacement of personal vehicles with shared-use vehicles on a detailed level. All papers that do compare this replacement rely on approximations of impacts, even when considering detailed logistics.

Evaluations of Environmental Impact of Grocery Delivery

The impact of substitution of personal grocery store travel by a delivery vehicle is a particularly well-studied example. The environmental impacts of grocery delivery services have received increasing attention in recent years as the availability of these services has risen, governments and consumers are increasingly concerned with climate change, and environmental evaluations of transportation has became more common. The literature to date indicates vehicle miles travelled (VMT) and CO_2 emissions are reduced when replacing personal travel for grocery shopping with delivery service. Most of this work has been done in Europe, and nearly all has occurred outside the United States. In addition, only one paper to date has explicitly examined the influence of routing and scheduling on environmental performance.

Cairns published a number of papers in the late 1990s illustrating significant VMT reductions over passenger travel associated with grocery delivery. Her work was based in the United Kingdom and examined different methods for calculating VMT impacts of grocery delivery services using approximations, bounding equations, and empirical models. Her empirical model (Cairns 1998) found VMT savings of up to 77% when 39 households are served by delivery vehicles with capacity to carry orders from eight households (a small delivery vehicle). Cairns (1997) found similar results, with at least 60% reductions in VMT estimated in every case, with many cases showing reductions on the order of 70%-80%. Cairns (1998) considered the number of customers served, finding increasing VMT savings were possible with an increasing number of customers. Her work did not consider environmental impacts, did not capture the impact of logistics decisions, and was based in Europe.

A Finnish research team has explored the logistics influences on VMT reductions potential (Punakivi and Saranen 2001, Siikavirta et al. 2002). This group has focused on how the interaction with the customer and the expected service parameters influence impacts, considering deliveries attended and unattended by customers, service time windows, and the mechanism for unattended deliveries. This work considers the financial implications of various methods as well as the transportation impacts. Their early work observed case studies with reductions in VMT between 50% and 93% over personal travel, depending on time window size. Siikavirta et al. (2002) took the evaluation a step further, adjusting VMT by emissions factors from the Finnish emissions model, LIISA, to illustrate an 18%-87% CO_2 emissions reduction potential when traditional grocery shopping was replaced by several different delivery service designs. Siikavirta et al.'s case studies (2002) resulted in estimates of CO_2 equivalent reductions of 76% with eight-hour time window services serving randomly-selected customers, and were able to increase these savings to 87% when the customers were organized by postal code (similar to the proximity-assigned analysis presented in this paper). Siikavirta et al.'s work (2002) is most similar to that presented here. Their research considers the CO_2 emissions impacts of routing and scheduling within an urban delivery system and provides an excellent point of comparison to the American case study presented here.

More recently, Tehrani and Karbassi (2005) used average emission factors (from Tehran's Air Quality Control Company) and trip lengths (from survey data) and focused on a busy, growing shopping district in Tehran, Iran. They found significant reductions in fuel use (88%) and emissions (25%) if all personal travel for grocery shopping was replaced with a delivery service. Tehrani and Karbassi's work provides insight into this problem in a non-Western context but is a strategic analysis that does not consider detailed impacts of density or routing.

As illustrated by the literature, significant mileage savings are possible when delivery service replaces personal travel. Further, one study (Siikavirta et al. 2002) examined the impact on CO_2 of replacing passenger travel with delivery service, and found significant CO_2 savings were also possible. These studies are summarized in Table 1.

Table 1: Summary of Literature Evaluating Mileage and CO_2 Emissions Reduction Potential for Grocery Delivery

	Analysis Unit	Savings	Scale	Method	Role of Logistics in Evaluation
Cairns 1997	VMT	≥ 60%, as much as 70-80%	Considers low adoption levels, small vehicles Truck capacity 5, 10, 15, 20	TransCAD routing, simple mathematical model	Fleet characteristics, load levels
Cairns 1998	VMT	≤77%	39 households Trucks capacity: 8 households	Empirical model in Excel, some data from TransCAD	Fleet characteristics, load levels
Punakivi and Saranen 2001	Km/order	54-93%	1450 households (1.63% market share) Truck capacity: 60 orders, 3000 litres	RoutePro simulations	Attended deliveries, unattended deliveries, delivery to centralized drop-off locations
Siikavirta et al. 2002	CO_2	18-87% 76% w/8-hour time window 87% proximity-assigned	1450 households (1.63% market share) Truck capacity: 60 orders, 3000 litres	RoutePro simulations, adjusted km by LIISA emissions factors	Time window size, proximity grouping
Tehrani & Karbassi 2005	Fuel use Emissions	88% 25%	2450 cars/day Average truck load: 30 orders, evenly distributed	Average emissions factors and trip lengths	none

METHODS

Network Dataset

The base network is from the ESRI StreetMap North America dataset (2006). These files include geographically accurate representations of the road network for North America, and include information regarding speed limit, functional class, street name, and street number range. The dataset was trimmed to only include road segments in the study area to reduce processing time, and the length in feet of each road segment was calculated and appended to the data table. Travel time was calculated using the segment length and these estimated speeds and also appended to the data table. Finally, information regarding the CO_2 emissions associated with each road segment for each vehicle type was also appended to the data table, based on the MOVES emissions factors, the roadway speed limit, the roadway functional class, the roadway length, and the vehicle type.

Emissions Factors

This research analyzes CO_2 tailpipe emissions and uses emissions factors obtained from the 2010 MOVES model (version MOVES2010) (US EPA 2010). This analysis assumed uncongested conditions, so speed limit data from the StreetMap North America dataset were used as the default flow speed for each road segment. Running exhaust emissions are tracked, since this problem involves less than one-hour stops. Based on EPA standards, an engine with its catalytic convertor in a hot state will pass to a cold state after this amount of time and will require accounting for hot- and cold-start emissions. However, stops in most residential urban pickup-and-delivery systems do not exceed this one-hour threshold. Data provided by a local carrier indicate the typical stop is less than five minutes.

Personal travel is represented by the emissions factors for personal cars using gasoline. A weighted average of the previous 15 years of data was used according to the distribution reported in the *Transportation Energy Data Book* (Davis and Diegel 2002). The delivery vehicle travel uses emissions factors for single-unit short haul trucks with diesel fuel, averaging emissions factors for 2007-2010 model years because the real-world fleet modelled here relies on a fleet of trucks less than three years old. In addition, the effects of refrigeration on emissions were not included since the fleet does not use refrigerated trucks.

Emission factors were selected for an analysis year of 2010. Hourly kilograms of CO_2 equivalents per mile were extracted and averaged over each hour of the day, for weekdays, throughout the year for the King County, Washington, region. All roadways in the region are urban. Roadways with speeds of 5, 20, 25, and 35 miles per hour are local or arterial roadways with frequent intersections and qualify as "unrestricted" roadways within MOVES. As such, these roadways were evaluated with MOVES' urban unrestricted roadtype emissions factors. Likewise, roadways with speeds of 45 and 55 miles per hour are limited-access highways, qualifying as "restricted" roadways, and therefore are evaluated with MOVES' urban restricted roadtype emissions factors (Table 2).

Table 2: Emissions Factors (Kilograms of CO_2 Equivalents per Mile) from EPA's MOVES Model

Speed	Road Type	Passenger Cars	Single-Unit Short Haul Truck
5	Urban Unrestricted	1.070268	3.713213
20	Urban Unrestricted	0.449884	1.441101
25	Urban Unrestricted	0.400271	1.272039
35	Urban Unrestricted	0.336501	1.014241
45	Urban Restricted	0.316466	0.865594
55	Urban Restricted	0.299489	0.739326

Grocery Store Locations

Puget Sound Regional Council provided a shapefile with the locations of the major grocery stores within King, Kitsap, and Snohomish counties. These locations were trimmed to those within one mile of Seattle. Stores within 1,000 feet of another store were eliminated, since they serve the same service area with competing brands. The resulting database included 42 grocery stores. The service areas of each of the remaining stores were calculated (using the Service Area tool within ArcGIS Network Analyst), and households were assigned to their appropriate service area.

This analysis considers replacing one roundtrip by a household to its nearest grocery store with delivery from that store. Cairns (1995) summarizes the results from six surveys to describe the

typical grocery shopping patterns in the United Kingdom. She cites a 1993 survey showing nearly two-thirds of housewives grocery shop less than two miles from home and a survey by Telephone Survey LTD, which indicated "62% of car shoppers use the nearest store to their home 'of its type' for main food shopping" (Cairns 1995, pg. 412). Her summary also indicated the vast majority of households with a car (99.6%) in the UK use a car for shopping, though in certain districts that percentage is somewhat lower (Cairns 1995). Siikvavirta et al. (2002) indicate in Finland only 55% of households use a car to grocery shop. Similarly, detailed data are not available in the United States, where the National Household Travel Survey (US DOT 2003) consolidates all shopping into one category. Analysis of the 2001 NHTS by Pucher and Renne (2003) indicates 91.5% of all shopping trips in the U.S. were made by personal automobile. Market research by the Nielsen Company indicates value is the primary consideration for 60% of U.S. shoppers when choosing a grocery store, followed by goods selection (28%) and closest store (23%) (2007). While value is considered more important than proximity for more Americans, the survey report did not indicate secondary and tertiary considerations. For this analysis, assigning customers to their nearest store is reasonable and provides a baseline for comparisons between personal travel and delivery vehicles.

Household Data

Geographic data regarding households and parcels were gathered from the Washington State Geospatial Data Archive (WAGDA) and the Urban Ecology Lab at the University of Washington. This effort required joining the WAGDA King County parcels file (containing address data) to the Urban Ecology Lab King County parcels file (containing the number of residential units data) to geocode the parcels with residential units information, and selecting out the residential parcels.

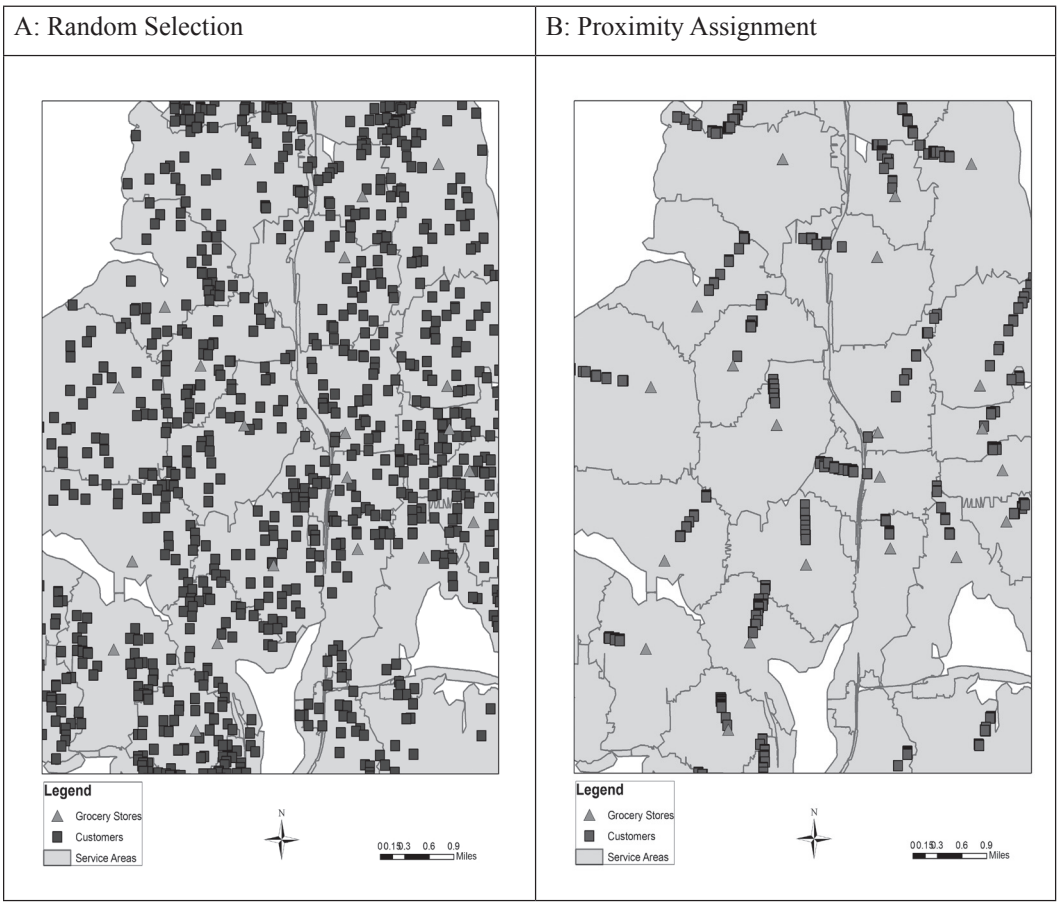
Calculating shared-use distance traveled is influenced by the logistical details of the service. Delivery service schedules dictated by customer preference have households distributed throughout the service area, while delivery service schedules dictated by the service provider have households geographically organized to obtain logistical efficiencies. Customer-directed service was estimated by random sampling of the households within the service area. Provider-directed service was estimated with proximity-assigned samples of the households. These two methods of selecting customers reflect best-case and worst-case scenarios in terms of logistical efficiency. Although a customer-directed service would allow customers to dictate their delivery time, a delivery service would assign customers to routes as efficiently as possible given fleet size and time constraints, so this worst case does not reflect the expected outcome in all cases. The provider-dictated service represents a best case for logistical efficiency with customers highly concentrated spatially.

Wygonik and Goodchild (2011) found truck size must be carefully calibrated to the customer volume to optimize cost and CO_2 emissions. As personal communication with local delivery providers indicate, each truck can hold approximately 35 households worth of orders, 35-household samples are used here. Because the sampling was done without replacement and the number of households in certain service areas was limited, five samples for each design were used, and their results averaged to provide the final values.

To sample the households randomly, the number of trucks (n) required to serve that service area was calculated by dividing the number of households in the service area (h) by the capacity of each truck (c=35). Because the base household parcel files were random, within each service area, every *n*th household was selected, for a total sample size of approximately 35 (minor variations resulted due to rounding). Each set included [i, n+i, 2n+i,…, xn+i] with i from 1 to 5.

To select a proximate sample of households, the households were ordered by their angle from the depot and then their distance from the depot. Households were then assigned to groups of 35 based on a modified greedy algorithm in which the next closest household was added to the sample until the desired sample size was achieved. Figure 2 illustrates the difference between the random sampling (Figure 2A) and proximity assignment (Figure 2B) for a set of service areas.

Figure 2: Illustrations of Sampling Techniques



Vehicle Travel

To estimate the distances traveled and the associated CO_2 emissions, routing tools within ArcGIS Network Analyst were used. These tools can optimize on any metric provided within the network, most frequently distance, time, or cost. Here they are extended to account for CO_2 emissions. While the exact details of the heuristic used in the ArcGIS software is proprietary, their help manual (ESRI 2010) indicates shortest paths are identified with Dijkstra's algorithm (Dijkstra 1959) and order sequencing is completed with a tabu search heuristic (Glover 1986). These solutions are well regarded for quickly producing reasonable results.

To complete the routing estimates, the Network Analyst Closest Facility tool was used to calculate the distance travelled to each grocery store for each household in the sample. Output from Network Analyst includes the one-way distance travelled for each residential unit and the one-way CO_2 emissions associated with each residential unit's grocery store trip when the trip is optimized for shortest time. These outputs were doubled, to reflect round trip distances and CO_2 emissions.

To complete the routing estimates, the Network Analyst Routing tool was used to calculate the distance travelled by a delivery vehicle starting and ending at the study grocery store and serving a sample of 35 households. Network Analyst was run to identify the fastest path to serve the given households. The analysis reordered the stops to identify the fastest route, but kept the first and last stops (the grocery store serving as the depot) constant. Output from Network Analyst includes the distance travelled for each delivery vehicle and CO_2 emissions associated with each tour, with the

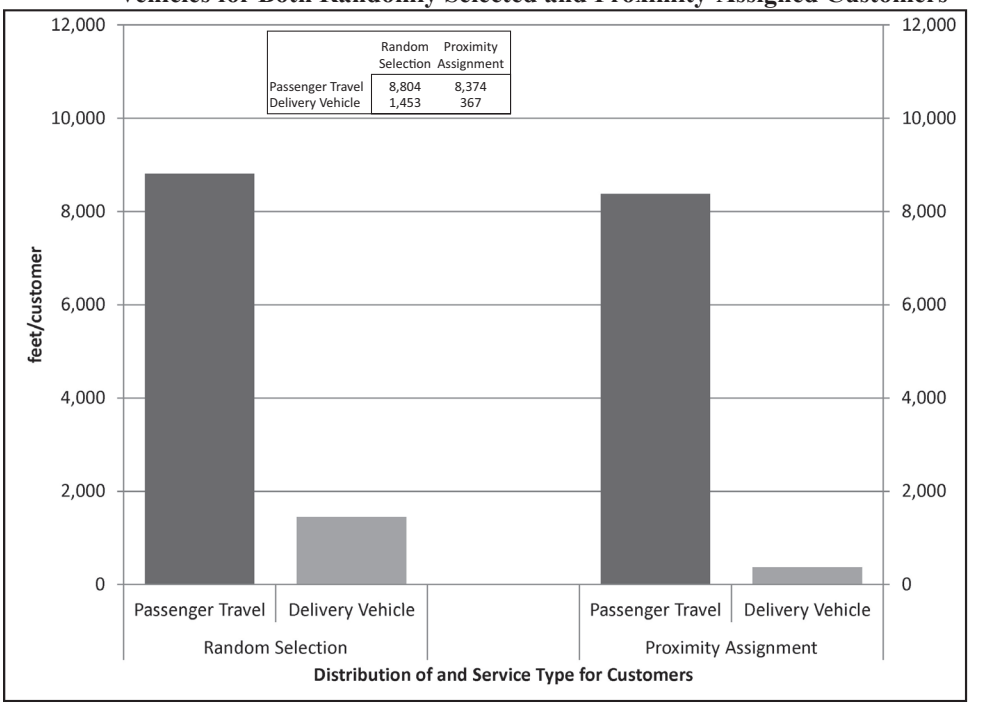
route optimized for shortest time. These values were averaged across the five samples to develop the total delivery vehicle miles traveled by the delivery vehicle for each service area.

RESULTS

Distance Traveled

The delivery vehicle routing, as expected, is shorter than the distance traveled by personal vehicles (see the table in Figure 3). The reductions in VMT of 85% to 95% are slightly higher than Cairns' (1997, 1998) observations between 60% and 80% and comparable to the upper bound of the Punakivi team findings of 54% to 93% (Punakivi and Saranen 2001, Siikavirta et al. 2002). While the distance traveled by the two subsets of personal vehicles (random selection versus proximity assignment) are reasonably similar, the distance traveled by the two subsets of delivery vehicles (random selection versus proximity assignment) are significantly different. Figure 3 illustrates this comparison, considering the variation across service areas.

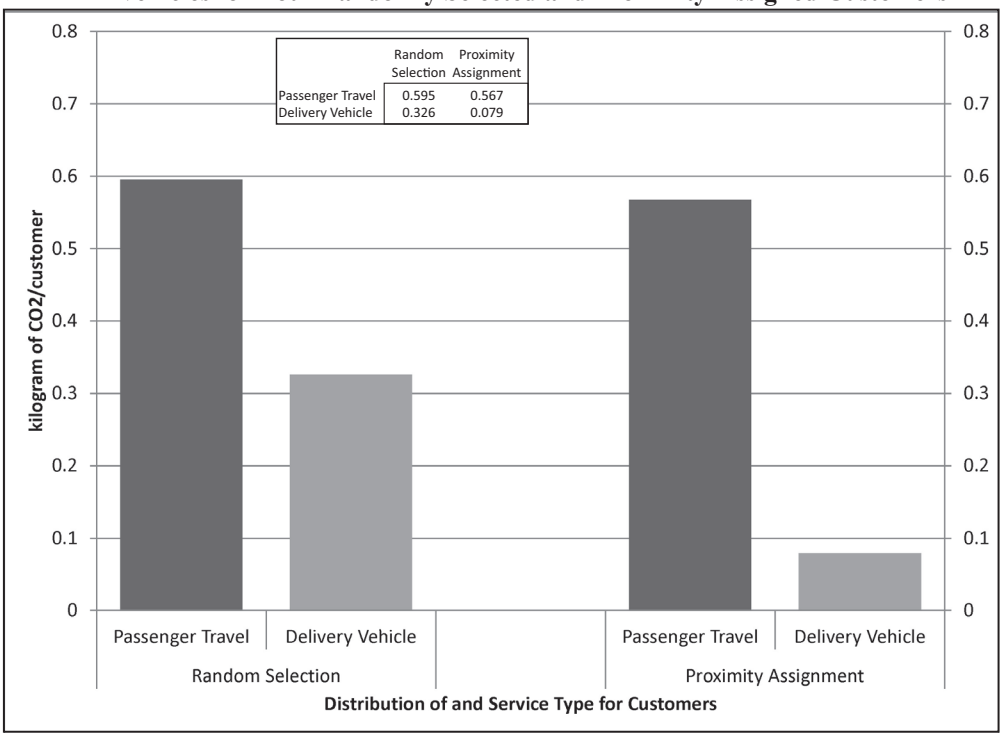
Figure 3: Comparison of Distance Traveled per Customer for Personal and Shared-Use Vehicles for Both Randomly Selected and Proximity-Assigned Customers



CO_2 Emissions Comparison

Also, as expected, the CO_2 emissions associated with the delivery vehicles are significantly fewer than those associated with personal travel (Figure 4). Large reductions in CO_2 emissions are observed when passenger travel is replaced by a delivery vehicle, and the results are comparable to Siikavirta et al.'s (2002) findings. However, these reductions are notably smaller than the reductions in distance traveled due to the larger CO_2 emissions associated with the delivery vehicles as compared with the passenger cars. As with distance traveled, the CO_2 emissions associated with personal travel do not vary significantly between the two sample types, but the CO_2 emissions associated with delivery travel do.

Figure 4: Comparison of Kilogrms of CO_2 per Customer for Personal and Shared-Use Vehicles for Both Randomly Selected and Proximity-Assigned Customers



The results illustrated in Figure 4 are presented as the upper and lower bounds of the benefit from a delivery service. Random selection represents a less efficient system, one in which customers select their service times. Even in this situation, delivery vehicles show significant reductions in CO_2 emissions over personal travel. In contrast, the proximity assignment selection represents a more efficient system, one in which the provider mandates service times, or can otherwise achieve significant customer density. The results from these two samples illustrate the influence logistics strategies have on the performance of a shared-use service. Appliance delivery with a small set of customers served on a given day is likely to roughly approximate a random sampling and is shown to have significant environmental savings. Grocery delivery services relying on a larger customer base and larger fleets will see reductions between these bounds, and services like garbage collection, in which customer service windows are frequently assigned by the provider and roughly approximate a proximity-assignment system, are shown to have higher environmental savings. This also demonstrates the importance of considering logistical strategies when estimating environmental impacts.

Influence of Service Area Size

While the above results support the findings from European research that significant VMT and CO_2 emissions reductions are possible when replacing personal travel with delivery service, given the vastly differing densities between European and American cities, the results were examined to determine if a relationship exists between CO_2 reduction and customer density. Given the fixed capacity of a delivery truck, the service area size represents the relative density of a service area. About half the variation in CO_2 emissions can be explained by service area for all but the randomly selected customers with delivery service. For all cases, a larger service area is associated with higher CO_2 emissions per customer.

Because of the higher CO_2 emissions associated with serving customers in a larger area, the CO_2 emissions savings associated with replacing personal travel with delivery service are higher as the service area increases (Figure 5a). This suggests the benefits of using a shared use vehicle are higher in less dense environments such as the U.S. Finally, comparing the service area size to the percentage reductions in CO_2 emissions (Figure 5b) illustrates the reductions associated with proximity assignment are consistent, between 80% and 90% (with one outlier of 70% savings). This result indicates density does not significantly affect the percentage reduction in CO_2 emissions and further indicates European and American results for proximity-assigned service should be consistent. Comparing these findings with Siikavirta et al.'s (2002) work, the values are similar (87% to the 80% to 90% observed here). The reductions associated with random assignment do increase with increasing service area, but also vary more, ranging from savings of 17.5% to 75%.

Overall, clear benefits are shown when personal travel is replaced by delivery service in all cases. This benefit is heightened when customers are grouped by location and when the service area is large. These results indicate density and urban form will influence the degree to which CO_2 emissions are reduced, but reductions should be expected in all situations where delivery trucks can be filled to capacity. Further study should examine the capacity level required to achieve a reduction in CO_2 emissions as most services are not expected to operate at full capacity at all times.

These savings assume households make round trips to the grocery store using a car. Other modes (for example walking, biking, or bus) are used and other destinations are included in grocery trips. Thus, a number of influencing factors, including trip chaining, mode choice, depot location, purchase/order size, congestion, and time of day, remain to be considered in the future.

CONCLUSION

The analysis of grocery delivery demonstrates that a significant reduction in vehicle miles traveled and CO_2 emissions is possible when personal vehicle travel is replaced by delivery service. We demonstrate that routing and scheduling strategy plays a significant role in this trade-off. These reductions are largest when the delivery service serves a proximity-assigned set of customers. In this case, delivery service can reduce CO_2 emissions by 80%-90%, compared with 17%-75% reductions when customers are randomly assigned. The results from this case study are consistent with Siikavirta et al.'s (2002) case study, which found CO_2 emissions reductions potential between 18% and 87%. Their largest reduction (87%) corresponded to the case in which customers were proximity-assigned, and is a very similar result to the 80% to 90% reduction observed here. This analysis considered the relationship between personal vehicle travel replaced by one delivery vehicle. This unit of analysis allows for scaling according to adoption level – even a small number of customers (35), if served by one truck, could result in reduced greenhouse gas emissions. It also reflects the efficiencies gained by larger customer populations served by a fleet of delivery vehicles. With an increasing number of customers, providers can serve customers with larger fleets (or larger vehicles), can improve logistical efficiency, and can reduce VMT per customer, such that the routes may emulate a provider-controlled, proximity-assignment service. In these situations, reductions in CO_2 emissions are expected to fall between the randomly-selected and proximity-assigned cases, since customers within a self-selected delivery window can be grouped by the provider into proximity-based routes.

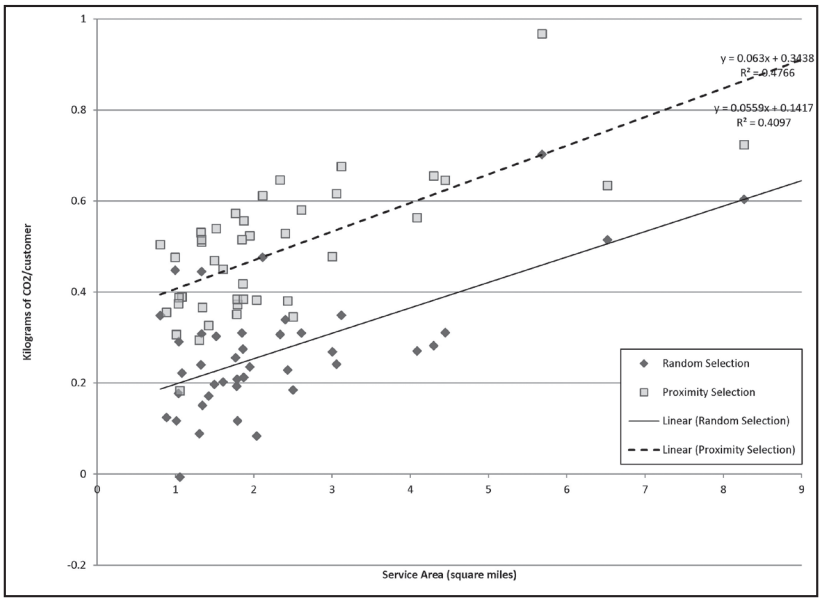
While all cases demonstrated reductions in CO_2 emissions, the largest savings in CO_2 emissions are associated with larger service areas. The profitability of delivery service is thought to correlate with dense locations, and larger service areas can be limited practically by service window size. However, emissions benefits are larger with less density. Pickup and delivery services could be incentivized in more rural locations to achieve environmental benefits, especially as alternative modes like transit, walking, and bicycle travel are less practical in more rural areas. In addition,

these results indicate some differences can be expected due to the density difference in Europe and the United States, but overall, these services should prove beneficial in both places.

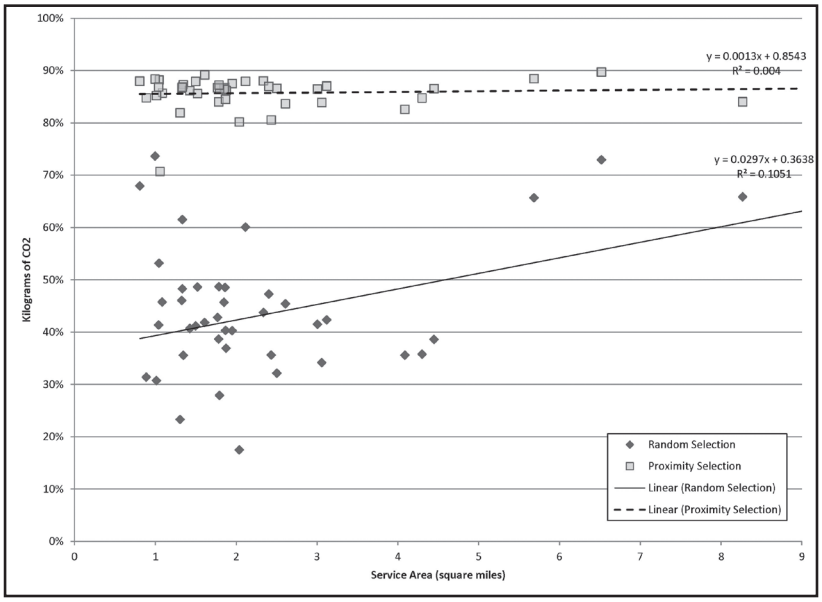
Significant greenhouse gas reductions are estimated through these cases, which provide initial bounds on expected gains from actualized service. The gains identified should be refined with further work to account for the reduction in impacts from personal travel associated with trip chaining, and the reduced benefit of delivery services when they operate at less than full capacity.

Figure 5: Comparison of Service Area to CO_2 Emissions Savings and Percentage Reduction, for Randomly-Selected and Proximity-Assigned Customers

A: Service Area Versus CO_2 Emissions Savings



B: Service Area Versus Percentage Reduction inCO_2 Emissions



References

American Public Transit Association (APTA). *2010 Transit Fact Book*, APTA, Washington, D. C., April 2010.

Barth, M.J., T. Younglove, and R.R. Tadi. "Emissions Analysis of Southern California Metrolink Commuter Rail." *Transportation Research Record: Journal of the Transportation Research Board*. Transportation Research Board of the National Academies, Volume 1520, (1996): 53-62.

Cairns, S. "Travel For Food Shopping: The Fourth Solution." *Traffic Engineering & Control* 36, (7/8), (1995): 411-14, 416-18.

Cairns, S. "Potential Traffic Reductions from Home Delivery Services: Some Initial Calculations." *TSU Working Paper* 97/45, 1997.

Cairns, S. "Promises and Problems: Using GIS to Analyse Shopping Travel." *Journal of Transport Geography* 6 (4), (1998): 273-84.

Cairns, S. "Delivering Supermarket Shopping: More or Less Traffic?" *Transport Reviews* 25(1), (2005): 51-84.

Davis, S.C., and S.W. Diegel. *Transportation Energy Data Book: Edition 22*. Oak Ridge National Laboratory, Oak Ridge, Tennessee. ORNL-6967, 2002.

Delucchi, M.A., Q. Wang, and R. Ceerla. "Emissions of Criteria Pollutants, Toxic Air Pollutants, and Greenhouse Gases, From the Use of Alternative Transportation Modes and Fuels." Berkeley: University of California Transportation Center, 2002, revision of 1996.

Dessouky, M., M. Rahimi, and M. Weidner. "Jointly Optimizing Cost, Service, and Environmental Performance In Demand-Responsive Transit Scheduling." *Transportation Research: Part D* 8 (6), (2003): 433-465.

Dijkstra, E.W. "A Note On Two Problems In Connexion With Graphs." *Numerische Mathematik* 1, (1959): 269–271.

Edwards, J.B., A.C. McKinnon, and S.L. Cullinane. "Comparative Analysis of the Carbon Footprints of Conventional and Online Retailing: A "Last Mile" Perspective." *International Journal of Physical Distribution and Logistics Management* 40, (2010): 103-123.

Environmental Systems Research Institute. *ESRI Data and Maps*. CD-ROM. Environmental Systems Research Institute, Redlands, California, 2006.

Environmental Systems Research Institute. *Algorithms Used by Network Analyst: Release 9.3*, 2010. http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?TopicName=Algorithms_used_by_Network_Analyst. Accessed June 25, 2010.

Gebresenbet, G., I. Nordmark, T. Bosona, and D. Ljungberg. "Potential For Optimised Food Deliveries in and Around Uppsala City, Sweden." *Journal of Transport Geography* 19, (2011): 1456-1464.

Glover, F. "Future Paths for Integer Programming and Links to Artificial Intelligence." *Computers & Operations Research* 13(5), (1986):. 533-549.

Hunt. J.D. and K.J. Stefan. "Tour-Based Microsimluation of Urban Commercial Movements." *Transportation Research Part B* 41, (2007): 981-1013.

Kim, J., M. Xu, R. Kahhat, B. Allenby, and E. Williams. "Design and Assessment of a Sustainable Networked System in the U.S.: Case Study of Book Delivery System." *Proceedings of the 2008 IEEE International Symposium on Electronics and the Environment*, 2008.

Matthews, H.S., C.T. Hendrickson, and D.L. Soh. "Environmental and Economic Effects of E-Commerce: A Case Study of Book Publishing and Retail Logistics." *Transportation Research Record: Journal of the Transportation Research Board*. Transportation Research Board of the National Academies, 1763, (2001): 6-12.

McKinnon, A. and J. Edwards. 2009. "Shopping Trip or Home Delivery? - Which Has the Lowest Carbon Footprint." *Logistics and Transport Focus* 11 (7), (2009): 20-5.

McKinnon, A.C. and A. Woodburn. "The Consolidation of Retail Deliveries: Its Effect on CO2 Emissions." *Transport Policy* 1, (1994): 2.

Newman, P. and J.R. Kenworthy. *Sustainability And Cities: Overcoming Automobile Dependence*. Island Press, Washington, D.C., 1999.

The Nielsen Company. "Good Value" is the Top Influencer of U.S. Grocery Store Choice." Press Release (2007). http://en-us.nielsen.com/content/dam/nielsen/en_us/documents/pdf/ Press%20 Releases/2007/December/%E2%80%9CGood%20Value%E2%80%9D%20Is%20the%20Top%20 Influencer%20of%20U.S.%20Grocery%20Store%20Choice,%20Nielsen%20Reports.pdf

Palmer, A. "The Development of an Integrated Routing and Carbon Dioxide Emissions Model for Goods Vehicles." Ph.D. Thesis: Cranfield University, 2007.

Pucher, J. and J.L. Renne. "Socioeconomics of Urban Travel: Evidence from the 2001 NHTS." *Transportation Quarterly* 57 (3), (2003): 49–77.

Punakivi, M. and J. Saranen. "Identifying the Success Factors in E-Grocery Home Delivery." *International Journal of Retail & Distribution Management* 29(4), (2001): 156-63.

Punakivi, M., H. Yrjola, and J. Holmstrom. "Solving the Last Mile Issue: Reception Box or Delivery Box?" *International Journal of Physical Distribution & Logistics Management* 31(6), (2001): 427-439.

Quak, H.J. and M.B.M. de Koster. "Exploring Retailers' Sensitivity to Local Sustainability Policies." *Journal of Operations Management* 25 (6), (2007): 1103.

Quak, H.J. and M.B.M. de Koster. "Delivering Goods in Urban Areas: How to Deal With Urban Policy Restrictions and the Environment." *Transportation Science* 43 (2), (2009): 211.

Shapiro, Robert, Kevin A. Hassett, and Frank S. Arnold. *Conserving Energy And Preserving The Environment.* American Public Transportation Association, Washington, D.C, 2002.

Siikavirta, H., M. Punakivi, M. Karkkainen, and L. Linnanen. "Effects of E-Commerce on Greenhouse Gas Emissions: A Case Study of Grocery Home Delivery in Finland." *Journal of Industrial Ecology* 6, (2002): 83-98.

Simon M., J. Alson, B. Ellies, and D. Ganss. "A Wedge Analysis of the U.S. Transportation Sector" Transportation and Climate Division, Office of Transportation and Air Quality, U.S. Environmental Protection Agency. EPA420-R-07-007, 2007.

Stefan, K.J., J.D. P. McMillan, and J.D. Hunt. "Urban Commercial Vehicle Movement Model for Calgary, Alberta, Canada." *Transportation Research Record: Journal of the Transportation Research Board* 1921, (2005): 1-10, Transportation Research Board of the National Academies, Washington, D. C..

Tanskanen, K., H. Yrjola, and J. Holmstrom. "The Way to Profitable Internet Grocery Retailing - Six Lessons Learned." *International Journal of Retail & Distribution Management* 30 (4), (2002):169-178.

Tehrani, S.M. and A.R. Karbassi. "Application of E-Commerce in Local Home Shopping and its Consequences on Energy Consumption and Air Pollution Reduction." *Iranian Journal of Environmental Science and Engineering* 2(4), (2005): 247-250.

United Nations. *Kyoto Protocol to the United Nations Framework Convention on Climate Change.* 1998.

United States Department of Transportation. *2001 National Household Travel Survey*. Washington, D. C., 2003.

United States Environmental Protection Agency. Office of Transportation and Air Quality. *MOVES (Motor Vehicle Emission Simulator) [2010 Model And User Guide]*, 2010. http://www.epa.gov/otaq/models/moves/index.htm. Accessed February 1, 2010.

Vincent, W. and L.C. Jerram. "The Potential for Bus Rapid Transit to Reduce Transportation-Related CO_2 Emissions." *Journal of Public Transportation* 9(3), (2006): 219-237.

Wygonik, E. and A. Goodchild. "Evaluating CO_2 Emissions, Cost, and Service Quality Trade-Offs in an Urban Delivery System Case Study." *IATSS Research*, (2011).

Erica Wygonik *is pursuing a Ph.D. in transportation engineering in the department of civil and environmental engineering at the University of Washington. She is interested in the relationship between land use and transportation and modeling of complex systems. Her current research focuses on ways to adapt the existing transportation system to reduce its environmental impacts through improved logistics and land use planning. She is also examining the benefits of replacing personal vehicle travel with home deliveries. Wygonik holds an M.S. in engineering (transportation) from the University of Washington, a B.E. from the Thayer School of Engineering at Dartmouth College, and a B.A. in cognitive science from Dartmouth College. Before matriculating at the University of Washington, Erica was a senior associate at Resource Systems Group, where she led the microsimulation and traffic operations practice areas. She is a licensed professional engineer.*

Anne Goodchild *has worked and studied in the transportation field for more than a decade. Her initial experience in management consulting for transportation providers was followed by the completion of a Ph.D. at UC Berkeley and research experience while developing the freight transportation program at the University of Washington. In addition to a B.S. in mathematics and an*

M.S. and Ph.D. in civil engineering, She completed minors in economics and operations research. She has a strong interest in the relationship between freight transportation activity, the environment, and the economy. This has led her to engage in many projects that are working to integrate business practice or shipper and carrier behavior, into freight transportation models, and seek environmental improvements that are economically efficient. Goodchild is chair of the Seattle Freight Advisory Board, and the paper review coordinator for the Freight Transportation Planning and Logistics, and Intermodal Committees of the Transportation Research Board.

Book Review

McDonald, Shannon Sanders. The Parking Garage: Design and Evolution of a Modern Urban Form. *Washington, DC: Urban Land Institute, 2007. ISBN 0874209986.*

The Parking Garage

by Mazhar Ali Awan

While many engineers, architects, economists, and transportation planners/designers concern themselves with the various modes of transportation (rail, bus, automobile, motorcycle, or air) and the concomitant infrastructure to get from point A to point B, few pay attention to the start or end of the trip. While not as "sexy" as creating and improving the links connecting the nodes, links quickly become inefficient and unproductive without attention to the start and end points. Shannon Sanders McDonald's *The Parking Garage: Design and Evolution of a Modern Urban Form* fills this gap directly while enlightening and entertaining the technical and lay reader.

McDonald takes the reader from the earliest parking needs of the early 1900s to the present day. She effortlessly melds architecture, engineering, and planning into a compelling story that addresses the evolution of parking garages (early elevator, ramp and self-park designs), congestion, urban sprawl and planning, quality of life and aesthetics, and larger issues. While there are other books on the design and development of parking facilities, McDonald's presents not only a macro-level view of what needs consideration in the design and function of parking garages, but precise and specific micro-level suggestions and requirements for optimal design from an architectural and urban planning perspective. The 10-chapter, 350-plus picture, 300-plus-page tome would be perfectly at home on a coffee table and delight and inform many a guest, or equally at home at an office desk to advise and inspire transportation professionals implementing such projects.

McDonald begins the journey with the automobile's place in the American city of the early 1900s. She notes that cars were a godsend to cities fighting problems such as pollution, diseases, and sanitation. She observes that electric vehicles were quite common and that drivers made use of charging stations at parking facilities of that time. McDonald explains that the primary difference between Europe and America in the introduction of the automobile and the concern over parking was that Europe had established cities and American cities were newer and had space for growth. McDonald cites that the earliest providers of parking for automobiles were horse stables converted to accommodate cars. These early providers grouped services under one roof, services such as upholstery, fuel, auto repair, and long-term storage. She notes seriously, yet humorously, that the first gas-powered car to drive down a street in the United States was in 1890 in Baltimore – and that the same car later burned down the building in which it was stored.

In the following chapter, McDonald covers the evolving early designs for this new type of building. She notes this as a fight between the ramp-based garage and the elevator-based garage. The elevator-based garage, which moved vehicles to floors and arranged them in an optimal manner, maximized the number of vehicles parked; however, it was slower than its rival ramp-based garage. McDonald, rightfully, makes short shrift of the elevator-based garage and notes its effective demise by 1925. She also notes that the ramp-based garage was less efficient (fewer cars per floor), but other features made it more attractive (reduced costs, faster ingress and egress, better fire protection, and improved visibility). The bulk of this chapter is about ramp-based garages—most notably, the D'Humy system, which increased the efficiency (cars per floor) of the ramp-based garage. She also comments on other ramp-based designs in this section.

In the subsequent chapter, McDonald writes:

> The early garage was a living place, simultaneously supporting the automobile user, other buildings, and the larger transportation system of the city. Unlike the stable or the carriage house, the garage played multiple roles and incorporated multiple functions, enjoyed synergistic relationships with many other building types, and was crucial to the economic and geographic growth of developing cities and towns.

She addresses how the garage fit in with multimodal facilities and how it became part of the cityscape. She provides multiple examples of the synergies associated with garages and other types of buildings such as courthouse, malls, stadiums, maintenance facilities, sales and showrooms, theaters, office spaces, banks, hospitals, airports, and colleges. Photo examples are peppered throughout the book.

McDonald addresses the form and function of garages next. She observes that they originally served multiple functions. In terms of form, as self-parking became more prominent, light and safety became an important part of the design. Post-9/11 security and signage gained a renewed importance and requirement in the design and renovation of garages. Environmental concerns brought forth gasoline, oil, and other chemical capture systems incorporated into garage design and function. In newer garages, McDonald notes, the incorporation of garage monitoring systems, parking revenue systems, HVAC, safety, and security systems. McDonald also addresses in detail garage construction and the requisite financing of building efforts.

Chapters 5 and 6 cover mechanization and engineering. McDonald observes that Chicago is the first city to incorporate parking into its transportation plans. She also addresses the differing types of garages (automatic, semi-automatic, and stackers) that exist, along with their requisite strengths and weaknesses. She notes almost (not quite fully) to the point of exhaustion, the engineering of parking garages and the subsequent advances over time as techniques evolved and new ones emerged.

Next, McDonald approaches the questions of why garages should be studied and how social and environmental connections can be maintained. There are two types of structures – one that is connected and fully integrated and one that is a separate unit. She elucidates on the importance of mixed use developments that incorporate parking seamlessly. She remarks on two types of connections for garages – one that is a transition point and one that is part of a transportation system. She laments that grand designs envisioned by architects and engineers were often not executed because of disregard for the importance of the building type and its function within the whole.

Frank Lloyd Wright notes that a building is not just a place to be; it is a way to be. McDonald takes this cue and focuses on the aesthetics of the garage by looking at the Beaux-Arts, Art Deco, Streamline Moderne, and Modernist approaches to garage design. Next, McDonald focuses on the incorporation of screens, facades, ornament, stairs, entry and exit points, art on and in the garage, and preserving the aesthetic of the location.

In the penultimate chapter, McDonald turns to parking in the urban planning context. She notes that parking is *the* urban planning issue. She observes that parking is encroaching on public lands and parks and affecting urban living. She covers the early attempts at regulation and the introduction of time limits, parking times, and street parking meters. She addresses the importance of multimodal transportation centers for the urban environment, transit systems, and efficient road networks. The demand for parking is driven by growth and prosperity and has resulted in sprawl. She notes two approaches to parking – *protection* of the city by helping to advance transit and *integration* by allowing cars to come inside the city as opposed to traversing on the outskirts and bypassing the city altogether. In this sense, McDonald posits we should return to the early multi-use parking facility typology.

McDonald closes with, "When designed as a discrete object, the building type emphasizes separation and segregation, but when designed as a part of the whole, the garage celebrates and confirms relationships and connections." She notes that the ultimate tension is between individualism and interdependence. She addresses sustainability, cars and the environment, parking

and community, and walking. In sum, the germ of the book is in promoting inclusion of the parking garage as part of a holistic approach to urban and transportation planning.

This reviewer believes that McDonald accomplishes the goals that she sets for herself in this book. She brings to the fore the reasons why parking in the planning context and the garage as a building type should be paid due deference in the overall overarching plans of city managers, transportation professionals, and those endeavoring to develop building projects within cities. Parking should not be an afterthought, nor should the garage be skimped on in terms of design effort and attention and share of finance for the total project. Even if one doesn't sit down to consume the whole text, the boxes within titled "Movement of Facts," "Past Lessons for the Present and Future," and other boxes on varying points are interesting nuggets of information. My lone complaint was that some text elaborating on the particulars of buildings lacked accompanying pictures that would have helped the reader greatly, but this occurs less than a half dozen times. McDonald clearly has a passion for her subject matter that shines through in a well-researched and well-documented manner.

Mazhar Ali Awan *is president and CEO of TEI, a consulting group founded in 2005. He previously served as an economist at the Surface Transportation Board and did graduate studies at George Mason University's School of Public Policy. Awan was formerly an economic adviser to the David Institute in Tustin, California, and worked as an engineer and project manager for various engineering consulting firms for over 12 years prior to entering the economics field. He holds a B.S. in economics and an M.A. in regional economic development and technology, cum laude, from George Mason University. Awan has published articles on various transportation-related issues and educational concerns.*

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

2011	Alan R. Bender
2010	B. Starr McMullen
2009	Richard Gritta
2008	Kenneth Button
2007	John (Jack) V. Wells
2006	Anthony M. Pagano
2005	Scott E. Tarry
2004	John S. Strong
2003	C. Gregory Bereskin
2002	Martin Dresner
2001	Mark R. Dayton
2000	Richard S. Golaszewski
1999	Aaron J. Gellman
1998	Richard Beilock
1997	Robert Harrison
1996	Clinton V. Oster, Jr.
1995	Paul K. Gessner
1994	Russell B. Capelle, Jr.
1993	Louis A. LeBlanc
1992	Stephen J. Thompson
1991	Joanne F. Casey
1990	Frederick J. Beier
1989	Thomas N. Harvey
1988	Joedy W. Cambridge
1987	Frederick C. Dunbar
1986	Carl D. Martland
1985	Allan D. Schuster
1984	Douglas McKelvey
1983	William B. Tye
1982	Michael S. Bronzini
1981	Jay A. Smith, Jr.
1980	Samual E. Eastman
1979	Lana R. Batts
1978	Carl J. Liba
1977	Gerald Kraft
1976	Edward Morlok
1975	Barry A. Brune
1974	Richard Shackson
1973	Harvey M. Romoff
1972	Arthur Todd
1971	Herbert E. Bixler
1970	Paul H. Banner
1969	George W. Wilson
1968	Donald P. MacKinnon
1967	David L. Glickman
1966	Edward Margolin
1965	Robert A. Bandeen
1964	Gayton Germane
1963	Herbert O. Whitten
1962	Herbert O. Whitten
1961	Herbert O. Whitten
1960	Herbert O. Whitten
1959	John Ingram (TRF of NY)
1958	Herbert O. Whitten (TRF of NY)

Recipients of the TRF Distinguished Transportation Researcher Award

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

2012	Kofi Obeng
2011	Anthony Pagano
2010	Captain James R. Carman
2009	John (Jack) Wells
2008	Gordon MacDougall
2007	Robert T. Beard
2006	Gene C. Griffin
2005	Michael W. Babcock
2004	Jack S. Ventura
2000	Paul K. Gessner
1998	Arthur W. Todd
1996	Stephen J. Thompson
1994	Samuel Ewer Eastman
1991	Carl D. Martland, C.E.
1990	Herbert O. Whitten, M.B.A.

Past Editors of JTRF

Wayne K. Talley (1998-2000)
K. Eric Wolfe (1993-1998)
Kevin H. Horn (1993-1998)
Anthony M. Pagano (1987-1993)
Richard Beilock (1987-1993)

Recipients of the TRF Best Paper Award

2012 Rafael Costa & C. Parr Rosson, III, *The Impacts of the Panama Canal Expansion on World Cotton Trade*

2011 Alexander Bigazzi and Miguel Figliozzi, *A Model and Case Study of the Impacts of Stochastic Capacity on Freeway Traffic Flow and Benefits Costs*

2010 Tony Diana, *Predicting Arrival Delays: An Application of Spatial Analysis*

2009 Tae H. Oum, Jia Yan, and Chunyan Yu, *Ownership Forms Matter for Airport Efficiency: A Stochastic Frontier Investigation of Worldwide Airports*

2008 C. Gregory Bereskin, *Railroad Cost Curves Over Thirty Years – What Can They Tell Us?*

2007 Rob Konings, Ben-Jaap Pielage, Johan Visser, Bart Wiegmans, *"Container Ports and Their Hinterland: Multimodal Access and Satellite Terminals within the Extended Gateway Concept"*

2006 Ian Savage, *Trespassing on the Railroad.*

2005 Patrick DeCorla-Souza, *A New Public-Private Partnership Model for Road Pricing Implementation.*

2004 Ian Savage and Shannon Mok, *Why Has Safety Improved at Rail-Highway Crossings*?

2000 Ian Savage, *Management Objectives and the Causes of Mass Transportation.*

1999 C. Phillip Baumel, Jean-Philippe Gervais, Marty J. McVey, and Takehiro Misawa, *Evaluating the Logistics Economic Impacts of Extending Six Hundred Foot Locks on the Upper Mississippi River: A Linear Programming Approach*.

1998 Carl Scheraga and Patricia M. Poli, *Assessing the Relative Efficiency and Quality of Motor Carrier Maintenance Strategies: An Application of Data Entry Envelopment Analysis*.

1997 Wayne K. Talley and Ann Schwarz-Miller, *Motor Bus Deregulation and Racial/Gender Effects: Earnings and Employment*.

1996 Todd Litman, *Full Cost Accounting for Transportation Decision Making: Estimates, Implications and Applications*.

1995 Leon N. Moses and Ian Savage, *A Cost-Benefit Analysis of United States Motor Carrier Safety Programs*.

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

1993 W. Bruce Allen and Dong Liu, *Service Quality and Motor Carrier Costs: An Empirical Analysis*.

1992 Victor E. Eusebio, Stephen J. Rindom, Ali Abderrezak, and John Jay Rosacker, *Rail Branch Lines at Risk: An Application of the Exponential Survival Model on Kansas Duration Data*.

1991 Patrick Little, Joseph M. Sussman, and Carl Martland, *Alternative Freight Car Maintenance Policies with Attractive Reliability/Cost Relationships*.

1990 James A. Kling, Curtis M. Grimm, and Thomas M. Corsi, *Strategies of Challenging Airlines at Hub-Dominated Airports*.

1989 Cathy A. Hamlett, Sherry Brennan, and C. Phillip Baumel, *Local Rural Roads: A Policy Analysis*.

1988 John R. Brander, B. A. Cook, and John Rowcroft, *Auctioning Runway Slots: Long Term Implications*.

1987 Clinton V. Oster, Jr. and C. Kurt Zorn, *Deregulation's Impact on Airline Safety.*

1986 Chulam Sarwar and Dale G. Anderson, *Impact of the Staggers Act on Variability and Uncertainty of Farm Product Prices*.

1985 Brian D. Adam and Dale G. Anderson, *Implications of the Staggers Rail Act of 1980 for Level and Variability of Country Elevator Bid Prices*.

Donald J. Harmatuck, *Back Haul Pricing: Mathematical Programming and Game Theory Approaches to Allocating Joint Costs*.

Jeffrey L. Jordan, Dieudonne Mann, S. E. Pressia, and C. Thai, *Managing the Transportation of Perishable Commodities: Temperature Control and Stacking Patterns*.

1984 K. Eric Wolfe, *An Examination of Risk Costs Associated with the Movement of Hazardous Materials*.

1983 Denver D. Tolliver, *Economics of Density in Railroad Cost-Finding: Applications to Rail Form A*.

1982 Jeffrey Beaulieu, Robert J. Hauser, and C. Phillip Baumel, *Inland Waterway User Taxes: Their Impacts on Corn, Wheat and Soybean Flows and Transport Costs*.

Journal of the Transportation Research Forum
Guidelines for Manuscript Submission

1. Submit manuscripts by e-mail or hardcopy to either General Editor at:

Michael W. Babcock
Co-General Editor, JTRF
Department of Economics
Kansas State University
Manhattan, KS 66506 U.S.A.
Phone: (785) 532-4571
Fax: (785) 532-6919
Email: mwb@ksu.edu

Kofi Obeng
Co-General Editor, JTRF
Dept. of Economics & Transportation/Logistics
School of Business and Economics
North Carolina A&T University
Greensboro, NC 27411 U.S.A.
Phone: (336) 334-7231
Fax: (336) 334-7093
E-mail: obengk@ncat.edu

2. E-mail submissions must be in MS WORD.

3. Final manuscript and abstract (hard or e-mail copy) must be received as soon as possible.

4. The text of manuscripts is to be double-spaced. Use one side of each page only. Articles are limited to a maximum length of 30 pages; industry issue papers and comments are limited to a maximum of 15 pages.

5. The manuscript should have a title page which includes the names, affiliations, address (mailing and e-mail) and phone numbers of all authors. Brief biographical sketches for all authors should be included with the manuscript.

6. The abstract should briefly describe the contents, procedures and results of the manuscript, not its motivation, and should not exceed 100 words.

7. Endnotes are to be used rather than footnotes, used sparingly and placed at the end of the manuscript. Do **NOT** use the endnote feature of the word processing software.

8. *The Chicago Manual of Style* is to be used for endnotes and references. At the end of the manuscript, complete references are listed alphabetically (not by number) by author surname, government agency, or association name. Use the following examples.

   Book:

   Jones, Robert T. *Improving Airline Transportation*. General Publishing Company, Washington, D.C., 2002.

   Chapter in a Book:

   Bresnahan, T.F. "Empirical Studies of Industries with Market Power." R. Schmalensee and R. Williq eds. *Handbook of Industrial Organization*. Amsterdam: North Holland (1989): 1011-1057.

   Journal Article:

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

   Journal Article with Multiple Authors:

   Chow, G., R. Gritta, and E. Leung. "A Multiple Discriminant Analysis Approach to Gauging Air Carrier Bankruptcy Propensities: The AIRSCORE Model." *Journal of the Transportation Research Forum* 31 (2), (1991): 371-377.

Ph.D Dissertation:

Jessup, E.L. "Transportation Optimization Marketing for Commodity Flow, Private Shipper Costs, and Highway Infrastructure, Impact Analysis." Dissertation (Ph.D). Washington State University, 1998.

Government Document:

U.S. Senate. Committee on Foreign Relations, *Investigations of Mexican Affairs*. 2 vols. 66th Cong., 2nd session, 1919-20.

9. Tables, figures, graphs, and charts should be titled and numbered by an Arabic numeral (e.g., Figure 2). All figures and charts should be submitted as **separate** files. Any graphics or photos must be 300 dpi and submitted as a separate .tif or .eps file.

10. Headings should adhere to the following style. Place the abstract below the title of the manuscript.

    • First level headings should be all caps, left justified.
    • Second level headings should be initial caps, left justified.
    • Third level headings should be initial caps on the same line as the first paragraph which it heads.
    • Do not number the headings.

11. Submit your final copy in "MS WORD" only.

12. For proper preparation of all charts, figures, maps and photos call Beverly Trittin, North Dakota State University, at (701) 231-7137 or bev.trittin@ndsu.edu prior to submitting the final version of your paper. The journal is printed in black and white, therefore, all graphics must be submitted in black and white, or grayscale.

    TIPS:

    - Photographs to be submitted as individual files at 250 dpi or higher resolution (.jpg or .tif format).
    - Images taken from the web are 72 dpi and are not acceptable for print. Secure high resolution
    - image when possible. Obtain permission for use of images taken from web.
    - Do not embed graphics in Word – submit as individual files (.jpg or .tif format).
    - Improper graphics or images will be returned to author for correct formatting.

Book Review Information

Books for review should be mailed to:

Dr. Jack Ventura
Book Review Editor
1025 Chiswell Lane
Silver Spring, MD 20901
Phone: (301) 593-1872
Email: jack.ventura@verizon.net

JTRF Information

The Journal of the Transportation Research Forum is distributed to members of the Transportation Research Forum.

ISSN 1046-1469

The Transportation Research Forum gratefully acknowledges the contributions of sponsoring and sustaining members.

2011-2012 Supporting Members

Michael Babcock, Kansas State University
Marcus Bowman, 3G Mobility, LLC
Michael Bronzini, George Mason University
Paul Gessner, Gessner Transportation Consulting LLC
Andrew Jennings
Elizabeth Ogard, Prime Focus LLC
Jack Ventura
John Wells, U.S. Department of Transportation