JOURNAL of the TRANSPORTATION RESEARCH FORUM

Volume 55, Number 1 Spring 2016

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

Journal of the Transportation Research Forum

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

Disclaimer:

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

Memberships/Subscriptions:

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

ISSN 1046-1469

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

or apply online at www.trforum.org

Journal of the Transportation Research Forum
Volume 55, Number 1 • Spring 2016

Table of Contents

On the cover: Southwest Airlines is an experienced hedger and uses financial instruments or hedging contracts to decrease its exposure to fuel price volatility. In "Airline Fuel Hedging: Do Hedge Horizon and Contract Maturity Matter?" Siew Hoon Lim and Peter Turner examine whether the length of hedging period and distance to contract maturity affect the effectiveness of jet fuel cross hedging.

BOOK REVIEW

A Message from the JTRF Co-General Editors

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

- Highway bridge component deterioration
- Driving knowledge and motor vehicle fatalities
- Airline fuel hedging
- Crop supply chain and transportation emissions
- Modified transportation systems and home location
- Multimodal connectivity of BRT stations
- Illumination of Overhead Guide Signs

In "Regression Model Evaluation for Highway Bridge Component Deterioration Using National Bridge Inventory Data," Pan Lu and co-authors develop an external validation procedure to quantitatively compare the forecasting power of different regression models for highway bridge component deterioration. They compared several regression models using the proposed procedure and traditional apparent model based on goodness of fit. The procedure developed by the authors has four steps, which are (1) select prediction analysis period, (2) data is segregated into two parts, one containing the latest data within the analysis period and the rest of the data used to develop regression parameters, (3) the predictive model is used to predict the data in the desired time horizon compared to the true data, which are the set-aside data and (4) the forecasting skill trend over time is analyzed.

Walter Simmons, Andrew Welki, and Thomas Zlatoper analyze the effect of driving knowledge on highway safety in "The Impact of Driving Knowledge on Motor Vehicle Fatalities." The authors estimate regression models on state-level data over the 2005-2010 period. The models contain a representative set of motor vehicle fatality determinants including driving knowledge. Driving knowledge is measured by performance on the GMAC Insurance National Drivers Test. The authors found that real per-capita income, precipitation, seat belt use, and a linear trend were negatively related to the motor vehicle death rate and are statistically significant. Also, the ratio of rural to urban driving, temperature, the percentage of young drivers, the percentage of old drivers, and alcohol consumption were positively related to the death rate and statistically significant. The authors found that the performance on the GMAC test has a statistically significant life-saving effect.

In "Airline Fuel Hedging: Do Hedge Horizon and Contract Maturity Matter," Siew Hoon Lim and Peter Turner examined weather the length of hedge horizon and distance to contract maturity affect the effectiveness of jet fuel cross hedging (some underlying asset highly correlated to jet fuel price). To answer the question in the title the authors examine the hedging performance of four common jet fuel proxies: West Texas Intermediate (WTI) crude oil, Brent crude oil (Brent), heating oil, and gasoil. The authors found that regardless of the distance to contract maturity, weekly hedge horizon has the best effectiveness for jet fuel proxies like heating oil, Brent, WTI, and gasoil. They found that heating oil is the best jet fuel proxy for all hedge horizons and contract maturities. Also the hedge effectiveness of heating oil is higher for one-month and three-month contracts.

T. Edward Yu and co-authors conduct a study that minimizes total cost for single feedstock supply chains for two dedicated energy crops in "Dedicated Crops Supply Chains and Associated Feedstock Transportation Emissions: A Case Study of Tennessee." The dedicated energy crops are perennial switchgrass and biomass sorghum. Using a spatial optimization model of greenhouse gas emissions from the transport of feedstock to the conversion facility were estimated for the respective feedstock supply chains. The authors found that different demand for land types of the two feedstocks and the geographically diverse landscape across the state affect the economics of bioenergy crop supply chains and feedstock transportation emissions. The authors concluded that switchgrass is more suitable than biomass sorghum for biofuel production in Tennessee based on the supply chains cost and feedstock hauling emissions.

In “Welfare Measures to Reflect Home Location Options When Transportation Systems Are Modified,” Shuhong Ma and Kara Kockelman examine the welfare (willingness to pay impacts) of transportation system changes. The authors do this by bringing residential location choice into a three-layer nested logit model to anticipate regional welfare impacts of transportation system shifts using consumer surplus. The model is applied to a sample of 60 Austin, Texas zones to estimate home buyers’ welfare impacts across various scenarios with different transit fares, auto operating costs, travel times, and home prices. The results suggest that new locators’ choice probabilities for rural and suburban zones are more sensitive to changing regional access, while urban and central business zone choice probabilities are more impacted by home price shifts. Also they noted that auto costs play a more important role in residential location choices in these simulations than those of transit.

Mintesnot Woldeamanuel and Craig Olwert develop a multimodality Index (MI) to evaluate the accessibility and convenience of transit use in “The Multimodal Connectivity at Bus Rapid Transit (BRT) Stations and the Impact on Ridership.” They point out that the integration of the Orange Line BRT system in Los Angeles with other travel modes, including bicycles, regular buses, and cars, was analyzed using field observations and LA Metro data to create an MI. The major objective is to determine if ridership is higher at stations with better multimodal connectivity. The authors found that multimodal connectivity varies across stations on the Orange Line BRT system. However, a positive relationship exists between ridership and the MI, indicating that MI is a reliable predictor of transit ridership and a useful tool for transit planning.

In “Effective Light Source for Illuminating Overhead Guide Signs and Improving Roadway Safety,” Mohammed Obeidat and Malgorzata Rys compare the illumination of five alternate light sources. The authors analyze the illumination of High Pressure Sodium (HPS), Metal Halide (MH), Mercury Vapor (MV), induction lighting and Light Emitting Diode (LED). The authors conducted a laboratory experiment to compare the light distribution of each light source. Also, a cost analysis was performed to compare initial, maintenance, and operating cost components of the light sources. The authors found that HPS was the optimum light source, and induction lighting was the least cost source of the five light sources and provided the best overall performance when considering initial costs, operating cost, expected maintenance, and sign illuminance.

Michael W. Babcock
Co-General Editor-JTRF

James Nolan
Co-General Editor-JTRF

Regression Model Evaluation for Highway Bridge Component Deterioration Using National Bridge Inventory Data

by Pan Lu, Shiling Pei, and Denver Tolliver

Accurate prediction of bridge component condition over time is critical for determining a reliable maintenance, repair, and rehabilitation (MRR) strategy for highway bridges. Based on bridge inspection data, regression models are the most-widely adopted tools used by researchers and state agencies to predict future bridge condition (FHWA 2007). Various regression models can produce quite different results because of the differences in modeling assumptions. The evaluation of model quality can be challenging and sometimes subjective. In this study, an external validation procedure was developed to quantitatively compare the forecasting power of different regression models for highway bridge component deterioration. Several regression models for highway bridge component rating over time were compared using the proposed procedure and a traditional apparent model evaluation method based on the goodness-of-fit to data. The results obtained by applying the two methods are compared and discussed in this paper.

INTRODUCTION

Bridge deterioration is a serious problem across the United States. According to the United States Department of Transportation (USDOT 2014), more than 604,000 bridges are located on public roads in the United States, with approximately 50% of them built before 1966 (during initial interstate highway construction). Bridges in this age group will reach their 50-year milestone in the next three years. Although 50 years was intended originally as the design life of many bridges, their service life can be extended through diligent maintenance and rehabilitation (Tolliver and Lu 2011). The efficient use of public funds for fixing and maintaining bridges to keep them in adequate condition requires an effective bridge asset management framework. To address this issue, transportation management agencies worldwide have begun to adopt bridge management systems (BMS). A BMS is used to determine the optimum future bridge maintenance, repair, and rehabilitation (MRR) strategy at the lowest possible life-cycle cost based on the forecasted bridge conditions (Frangopol et al. 2000).

In the United States, highway bridge ratings typically consist of three major components: deck, superstructure, and substructure. The components deteriorate as a result of operating conditions and external environmental loads. Because of the importance of these components for normal operation and safety, prediction models for component deterioration are routinely developed to assess the conditions of bridges for a given future time span.

Among all predictive models, regression models are the most widely adopted types for engineering applications (FHWA 2007). Regression models forecast future bridges' performances from a set of explanatory variables via equations developed based on past data.

Specifically for bridge condition prediction, as stated by J. Lee et al. (2008), the major challenge faced by current bridge deterioration modeling techniques is the lack of reliable prediction modeling of future bridge condition ratings. For a given set of past bridge condition data, researchers can potentially apply all the predictive models that are selected based on in-sample goodness-of-fit statistics, and it is likely that predictions from all these models will be different. This presents a difficulty with regard to BMS because these different prediction results can lead to different management strategies. From an end-user perspective, no matter how complicated or simple the models are, prediction accuracy is the most important characteristics of the model. Thus the selection of predictive models should not be based on the modeler's experience or the model goodness-of-fit with respect to in-sample data, but on the model's ability to accurately predict future behavior. This study will develop and apply an objective model evaluation procedure to reveal the true forecast power of the bridge component regression models so that engineers and decision makers can use this approach to gain confidence in bridge deterioration prediction. No existing literature has addressed this issue. The proposed procedure will be applied to the comparison of two regression models constructed using bridge component rating data in Illinois.

LITERATURE REVIEW

Regression model forecast verification is sometimes called validation, or evaluation. The purpose of this process is to help assess the specific strengths and deficiencies of regression models when they are used to forecast values of the dependent variable using forecasted values of the explanatory variables. This process has the potential to justify uses of the model for forecasting and support better decision making (Wilks 2006). Depending on the process used in validation, there are three types of evaluation procedures: apparent, internal, and external (Steyerberg and Harrell 2014). Apparent validation validates a model's goodness-of-fit on the entire dataset used to construct the model, which may not reveal the true predictive ability of the model because the exact same dataset is used for model development and validation test. The estimation of the prediction ability has been shown to be overly optimistic with this validation method (Witten and Frank 1999).

Internal validation evaluates sample data from the same underlying population as the sample data used to develop the model. Usually, it is difficult to obtain new sample data from the same population for validation. In the literature, the most commonly found method for internal validation is data-splitting (McCarthy 1976; Clementi et al. 2001; Shao 1993; Snee 1977; Lu and Tolliver 2012).

Simple data splitting is a subsampling procedure also known as resampling. It re-sizes the sample data into two sub-datasets and uses one random subset for validation and the other for model development. There are several data-splitting techniques found in literature (Snee 1977): 1) Cross validation is a repeated data-splitting technique, it repeats the simple data-splitting analysis many times and the predictions are averaged. 2) The bootstrapping procedure is different from splitting in that bootstrapping samples are taken with replacements from the original sample while data-splitting samples are selected without replacement. 3) The jack-knife technique is very similar to repeated data-splitting except it only takes one of the records from the original sample out at one time and repeated as many times as the total number of records in the original sample.

These procedures are powerful techniques when external validation is not possible. However, external validation is the most accurate and unbiased test for the model and the entire data collection process as stated by Harrell et al. (1996). External validation's main emphasis is that predictions from the previously developed model are tested on a new dataset that is different from the development population.

In the following sections, it will be shown that the data-based procedure proposed in this study can also be considered as a type of external validation with time delay and will reveal the model's true forecasting power in the past. The procedure is unique in that it focuses on long-term prediction power evaluation, which has not been investigated extensively in engineering applications. Several key prediction accuracy measures will be used in the examples and are introduced in this section.

DATABASE

The National Bridge Inventory (NBI) ASCII database is a unified database compiled by the Federal Highway Administration (FHWA) for all bridges and tunnels in the United States that have public roads passing above or below (FHWA 2007).The database provides information on 116 items and 432 characteristics of each bridge, including, but not limited to, bridge type and specification, bridge geometric information, bridge functional description, operational condition, bridge inspection data, and bridge construction and reconstruction records. The detailed information for each item and characters can be found in the FHWA NBI reference report (FHWA 1995). The data in NBI is collected by state highway agencies and reported to FHWA annually.

Within NBI inspection data, there are three primary component ratings of special importance to bridge asset management: deck condition rating (DCR), superstructure condition rating (SPCR), and substructure condition rating (SBCR). The NBI rating system includes eight interim levels between excellent (9) and failure (0). For detailed information regarding to NBI inspection data, viewers are referred to NCHRP (2009).

METHODOLOGY

Prediction Accuracy Measures

Cook and Kairiukstis (1990) state that reduction of error (RE) "should assume a central role in the verification procedure" (p. 181). RE is an example of a forecast skill statistic (Wilks 2006). Wilks (2006) defined forecast skill as the relative accuracy of a set of forecasts with respect to some set of standard controls, which are usually the average values of the predictions. The equation used to calculate RE can be expressed in the following Equation (1).

(1) $$RE=1-\frac{SSE_v}{SSE_{ref}}$$

Where SSE_v = sum of squares of validation errors between observed and predicted values over the validation period and SSE_{ref} = sum of squares of validation errors between observed values and mean of the predictions often known as control values or reference values over the validation period.

The difference between observed and predicted values is defined as validation error noted as $e_{(i)}$. It can be mathematically expressed as Equation (2).

(2) $$e_{(i)} = y_i - \widehat{y_{(i)}}$$

Where y_i and $\widehat{y_{(i)}}$ are the observed and predicted values of the predictions for validation data point i.

The sum of the squares of errors for validation, SSE_v, can be expressed as Equation (3) and the sum of squares of errors for reference, SSE_{ref}, can be expressed as Equation (4).

(3) $$SSE_v = \Sigma_{i=1}^{n_v} e_{(i)}^2$$

(4) $$SSE_{ref} = \Sigma_{i=1}^{n_v} (y_i - \bar{y})^2$$

Where n_v is the total number of data points in the validation dataset and $\bar{y}$ is the mean of the predictions, which usually serves as a reference or control value. Theoretically, the value of RE can range from negative infinity to one, where one indicates perfect prediction for the validation data set. It will only occur when all the residuals for validation data are zero. On the other hand, if SSE_v is much greater than SSE_{ref}, RE can be negative and large. As a rule of thumb, a positive RE indicates that the regression model on average has some forecast skill. Contrastingly, if RE ≤ 0, the model is deemed to have no skill to predict (Wilks 2006; Cooks and Kairiukstis 1990). The similarity in form of the equations for RE and regression R^2 expressed as Equation (5) suggests that RE can also be used as validation evidence for R^2. The closer the values of RE and R^2 are to each other, the more the model is accepted as a predictive tool.

(5) $$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2}{\Sigma_{i=1}^{n}(y_i - \bar{y})^2}$$

In this research, adjusted R-squared is reported to take account of the phenomenon of the R-squared automatically and spuriously increasing when extra explanatory variables are added to the model. Adjusted R-squared can be written as Equation (6).

(6) $$R^2 = 1 - \frac{SSE/df_e}{SST/df_t} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2/(n-p-1)}{\sum_{i=1}^{n}(y_i - \bar{y})^2/(n-1)}$$

Other commonly used apparent model validation criteria, including Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC), and Mean Absolute Error (MAE), are also selected in this research and compared with the RE external model evaluation method. The model with the smallest AIC, BIC, and MSE is deemed the "best" model based on apparent validation since it minimizes the difference from the given model to the "true" model. In other words, that smaller AIC, BIC, or MSE indicates better model/predictor. They can be mathematically expressed as Equation (7), (8), and (9).

(7) $$AIC = n * \ln\left(\frac{SSE}{n}\right) + 2k$$

(8) $$BIC = n * \ln\left(\frac{SSE}{n}\right) + \frac{2(k+2)n\sigma^2}{SSE} - \frac{2n^2\sigma^4}{SSE^2}$$

(9) $$MSE = (\sum_{i=1}^{nv} e_i^2)/n$$

Where n is in-sample size, SSE is the sum of the squares of errors, e_i is validation error, k is the number of independent variables, MSE is mean squared error, and σ^2 is error variance.

Forecasting Power Evaluation Procedure

For a predictive model, it is critical to have a quantitative measure of prediction accuracy. More important, given the many similar regression modeling choices, the user needs to be able to tell with confidence which model will yield the best prediction over a given period of time, which can be the analysis period. The deterioration of a bridge is a relatively slow process. With bridge rating indicators collected annually, it is difficult to detect any trend unless one uses data over a long time span. If all existing data are used to construct the model, there will be no independent data left for validation purposes. In this study, it is proposed to artificially "reserve" part of the data as the independent validation "pool" (external data) to use in evaluating long-term regression model quality. Splitting the existing dataset for this process can be application-specific. For example, if it is of interest to a transportation agency to predict bridge condition in five years, the validation datasets should cover at least five years of data to reflect the prediction span, which will at least provide the forecasting power within the analysis periods.

The procedure is rather straightforward and can be summarized in four steps: (1) A user select prediction analysis period that is typical for the implementation of the model of interest. (2) Data should be segregated into two parts, one containing the latest data at least within the analysis period identified in step 1, which will be kept unused during the development of the model, with the rest of the data used to develop regression parameters for the selected model of choice (assuming regression models are used). The data set aside will provide forecasting accuracy validation information for the time horizon that is at least the same as the analysis period. (3) The predictive model and its variations (may include other model types also) will be used to predict the data in the desired time horizon and compared to the true data, which is the set-aside data. Based on this comparison, a group of physically meaningful indicators can be derived (based on the application of the model prediction) for the quality and accuracy of the model. (4) Based on these indicators, the forecasting skill trend over time is analyzed and the forecasting model selection is judged based on the analysis results. In short, this approach essentially "rolls back" the modeler in time, assuming the prediction was done N years ago (N is the needed prediction time span) without knowing the current data. However, the forecasting model is selected by using the current data. The resulting best model is truly the best model N years ago. As a result, presumption of the procedure is that the model that performs well N years ago will continue to perform well N years in the future.

This presumption brings about the limitation of using this approach: The interactive mechanism between independent variables and dependent variables needs to be close to stationary over the prediction time span. Or in other words, the prediction accuracy of the model will not change dramatically over time. For example, if a phenomenon was affected by certain factors (independent variables) that were not present in the past (e.g., adoption of a new bridge design detail, new deicing chemical), this approach will not apply. However, under such conditions, almost all statistical regression approaches will be invalid as that piece of information does not exist in any data pool. In such cases, only the physically or mechanistically derived models can be used for prediction. The proposed approach should have very accurate results for any process that has a stationary underline-driven mechanism, i.e., the influence of independent variables on the dependent variables does not change dramatically with time. Even for cases where the internal driven mechanism does change over time, as long as the change is slow relative to the prediction time span, the approach could still be used in a piece-wise linear fashion where only the portion of the data closest to the prediction time span is used to construct the model. It is envisioned that this approach can be applied to many engineering problems to assist decision making.

BRIDGE RATING PREDICTION MODEL EVALUATIONS AND FINDINGS

Bolukbasi et al. (2004) recommended bridge component deterioration models with third-degree polynomial functions of bridge age. The research developed third-degree polynomial regression models with 2,601 Illinois bridge NBI inspection records from 1976 to 1998 and recommended that the data should be filtered by eliminating bridges for which reconstruction works are not recorded.

To illustrate the application of the proposed procedure, two candidate regression models for predicting steel bridge deck component ratings performance in Illinois were evaluated and compared by both in-sample goodness-of-fit statistics as apparent validation method and the data-based prediction power evaluation procedure as external validation method. One of the prediction models duplicates the work of Bolukbasi et al. (2004) with and without a filtering process. The filtering method is based on trends in rating values. If the data show an increase in the value of the condition rating, then unrecorded repair and/or reconstruction activity is assumed and the data observation is deleted. For detailed filtering method, readers are referred to Bolukbasi et al. (2014). Steel bridge deck deterioration models are constructed based on Illinois NBI data from 1994 to 1999. The same data set is used to construct the other multiple linear regression model through an explicit enumeration of all possible independent variables to the best knowledge of the authors. Both regression models will be based on the dataset with and without a filtering process, so for comparison, there will be four models: polynomial model (Bolukbasi et al.'s third degree polynomial regression model) with a data filtering process, polynomial model without a data filtering process, full model (multiple linear regression model) with a data filter process, full model without a data filtering process. Illinois NBI bridge population data from 2000 to 2014 is set aside for the purpose of external data validation.

This example looked at the accuracy of various models in a 15-year prediction horizon, with some interesting observations obtained and discussed in this paper.

Overview of Models and Comparison

Regression models for bridge component deterioration are used by many transportation agencies to assist in bridge inventory management. In research on this subject, a few key explanatory variables were found to influence the prediction accuracy. These include the age of the bridge, traffic load, jurisdiction of the bridge, and deicing practices, just to name a few. A multiple linear regression model is constructed through an explicit enumeration of all possible explanatory variables available to the authors, and the "best" fitted model is selected based on model selection and is referred to as the "full" model afterward. The "full" model has "age" as continuous independent variable, traffic (Average Daily Traffic [ADT]) and bridge design as categorical variables. Traffic, ADT, can be forecasted with various travel demand models and adjusted by seasonal, directional count data. In the United States, prototypical vehicles are defined for analyzing bridge load designs. The alphanumeric codes “H” or “HS” denote a single-unit truck and a tractor pulling a semitrailer, respectively. The numeric suffix represents the gross weight in tons for H truck or weight on the first two axle sets of the HS truck. For example, H_10 denotes a truck with a gross weight of 10 tons. A duplication of the work of Bolukbasi et al. (2004) to construct a third degree polynomial model is also selected for the purpose of comparison and refers to “polynomial” model. Both two models are constructed based on the data set with and without filtering process. In this study, both apparent and external validation will be performed for both “full” and “polynomial” models, and the indicators described in earlier sections will be used to evaluate model quality.

First, two sets of regression models were constructed as shown in Table 1 and some selected apparent model validation indicators, adjusted R-squared, AIC, MSE, and BIC, are also shown in Table 1. One can tell that model constructed with data filtering has smaller AIC and BIC values and larger adjusted R-squared values by comparing column 2 and 3 for polynomial model and column 4 and 5 for full model. This finding conforms with Bolukbasi et al. (2014), so the data filtering process to remove unrecorded rehabilitation or reconstruction effects is needed before model construction.

Full models are more likely to be selected over polynomial models based on larger adjusted R-squared value, smaller MSE values, and smaller AIC and BIC values with respect to apparent validation criteria by comparing column 2 and 4 for adjusted data set and column 3 and 5 for unadjusted data set. Note that the full model contains polynomial model, and, based on apparent validation criteria, the full model is believed to be the best model and is preferred.

Note that even the full model only has 35% of variances explained by the independent variables, that is because many variances that could cause the bridge deterioration are not available and excluded in the model, such as climate information and maintenance funding level status. The apparent evaluation method is designed to identify significant explanatory factors and can select the best-fitted model for the sample data. However, it is still questionable if the model selected by the apparent validation method is suitable for short- and long-term forecasting. In other words, the model with the highest R-squared may not yield the best forecasting results.

Model Validation and Comparison Results

Once the regression model apparent validation analysis was done using all Illinois NBI 1994-1999 data and the NBI datasets from 2000-2014 were kept as the external validation data pool; model external validation can be performed and analyzed by using the RE indicator. The validation datasets can be considered external datasets for three reasons: 1) NBI reports data annually in separate datasets that will lead to differences in various aspects of the data such as data collection techniques, data collection personnel, and possibly the definition of variables. 2) the bridges included in validation datasets and model construction data sets vary because bridges may be closed or open to traffic for various reasons in different years. 3) NBI inspection records in each single year contain the whole bridge population information but not sample information.

To illustrate the external validation method result, both deck models constructed with a data filtering procedure to remove unrecorded rehabilitation or reconstruction effects are compared with prediction power indicator, RE. As shown in Table 2, RE values for both models are calculated for each validation data set.

Table 1: Parameter Estimates and Statics with Data of 1994-1999

Deck Model	Polynomial model with data filtering	Polynomial model without data filtering	Full model with data filtering	Full model without data filtering
N	20643	63439	20643	63439
Adjusted R-squared	0.3258	0.2686	0.3561	0.2967
AIC	15573	38767	14637	36284
MSE	2.13	1.84232	2.03079	1.7717
BIC	15575	38769	14639	36286
Intercept	8.2709	8.19543	7.85967	8.0987
Age	-0.08254	-0.095	-0.09026	-0.10561
Age²	0.00097214	0.00123	0.00128	0.00148
Age³	-0.0000053	-0.00000613	-0.00000723	-0.00000754
ADT<=1000	N/A	N/A	-	-
ADT<=5000	N/A	N/A	-0.36832	-0.27658
ADT<=10000	N/A	N/A	-0.43792	-0.44108
ADT>10000	N/A	N/A	-0.64814	-0.44701
H_10	N/A	N/A	0.68265	0.47337
H_15	N/A	N/A	0.68574	0.45804
H_20	N/A	N/A	0.62199	0.45024
HS_15	N/A	N/A	0.90066	0.83339
HS_20	N/A	N/A	0.84992	0.51066
HS_20P	N/A	N/A	0.74399	0.35579
HS_25	N/A	N/A	-	-

Note: "N/A" indicate that the corresponding variables are not considered in the model; "-"indicate that the corresponding variable is a reference variable for the categorical variable; all independent variables are significant at 99% of confidence.

Table 2: Reduction of Error Forecasting Power with Data of 2000-2014

Obs	Year	Observations	Full Model RE	Polynomial Model RE	RE Difference
1	2000	5491	0.26985	0.24409	0.026
2	2001	7219	0.25568	0.24016	0.016
3	2002	7122	0.21916	0.20442	0.015
4	2003	7034	0.20004	0.19137	0.008
5	2004	6943	0.21934	0.21097	0.008
6	2005	6869	0.20258	0.19101	0.012
7	2006	6763	0.19298	0.18161	0.011
8	2007	6707	0.17798	0.16430	0.014
9	2008	6664	0.17893	0.16412	0.015
10	2009	6631	0.19466	0.18045	0.014
11	2010	6630	0.17018	0.16121	0.009
12	2011	6680	0.18777	0.18349	0.004
13	2012	6660	0.18815	0.18490	0.003
14	2013	6664	0.18011	0.18374	-0.004
15	2014	6601	0.14751	0.15336	-0.006

One can tell from Table 2 that there are 15 external validation datasets and the data size ranges from 5,491 to 7,219. As stated earlier, an RE of 1 indicates perfect prediction for the validation dataset. As a rule of thumb, a positive RE indicates that the regression model, on average, has some forecast ability with higher values indicating better forecasting, and the closer the values of RE are to each other, the more the model is accepted as a predictive tool (Wilks 2006; Cooks and Kairiukstis 1990). Both models' RE values start at values close to, but less than, the models' adjusted R-squared value: 0.26985 vs 0.3561 (0.086 difference) and 0.24409 vs 0.3258 (0.082 difference). The finding shows that the evaluation adjusted R-squared factor provides close estimation of the true prediction accuracy for the example models at the beginning of the validation years, but the adjusted R-squared evaluation might be optimistic for forecasting power, especially for long-term analysis.

RE values all are positive, indicating a certain level of forecasting power, which is promising with the true external observations. The full model has a relatively higher forecasting power when compared to the polynomial model for the first 13 years, and then the polynomial model shows a higher forecasting power for the 14th and 15th years. In general, the forecasting power difference between the two models, column 6, shows that forecasting power of the two models decreases over the 15 validation periods. This finding indicates that the full model may be the preferred model to forecast near-term condition; but for long-term forecasting purpose, e.g., forecasting condition over 10 years, the polynomial model may be preferred.

Reasons for this can be that apparent validation selects the full model by best describing the interactive mechanism between independent variables and dependent variables for the same sample dataset used to build the model. However, when applying the model forecasting ability to a future dataset, the interactive mechanism between independent variables and dependent variables may be unchanged over the short prediction time span but may change for a longer prediction period. The full model involves more independent variables than the polynomial model (which only involves one variable, age), and the likelihood that certain factors included in the full model will change in long time span is higher than in the polynomial model. When that happens, the full model loses its forecasting power compared to the polynomial model or, in other words, the full model introduces more errors than the polynomial model.

Also note that by examining RE values for both models by year, column 4 and column 5 from Table 2, one can tell that forecasting power represented by RE can both increase and decrease for a short time, but in general and overall, the forecasting power decreases over the long term.

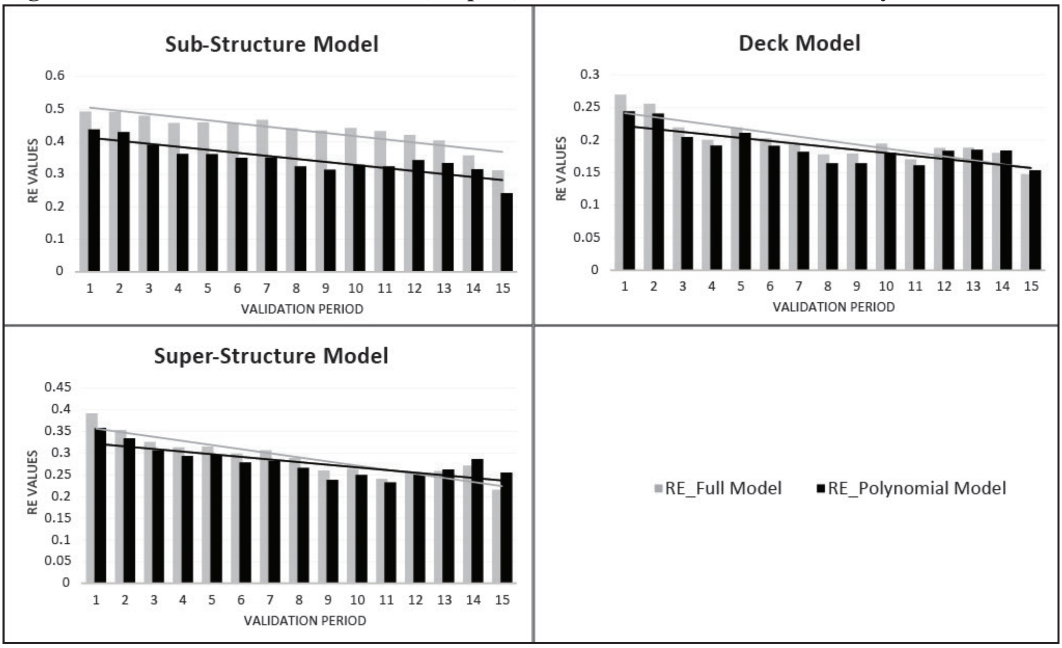
To further illustrate the forecasting ability of the two models, the authors repeat the proposed procedures for both superstructure and substructure models with a data filtering procedure considered. The apparent validation results are shown in Table 3, and external validation results are shown in Figure 1. From Table 3, the full model is preferred according to the apparent validation method for both substructure and superstructure models with higher adjusted R-squared, smaller AIC, smaller MSE, and smaller BIC values.

Table 3: Sub- and Super-Structure Model Statics with Data of 1994-1999

Deck Model	Substructure Polynomial model	Substructure full model	Superstructure Polynomial model	Superstructure full model
N	20643	20643	20643	20643
Adjusted R-squared	0.4287	0.4949	0.4225	0.4660
AIC	15853	13322	13668	12068
MSE	2.155	1.91	1.94	1.79
BIC	15855	13324	13670	12070

Shown from Figure 1, RE values for all models show up-and-down patterns in the short-run; however, they all show decreasing trends over the 15 validation periods. The full model is preferred at the beginning and the polynomial model shows better forecasting ability at validation years 13 and 14, respectively, for deck and superstructure models. For the substructure models, the full model is preferred over the 15 validation periods. Note that to determine the “best” model for its forecasting ability, especially for long-term planning, external data evaluation with roll-back data is recommended. External data evaluation will result in a different model preference compared with apparent model validation method.

Figure 1: Reduction of Error for Deck, Super-, and Sub- Structure Full and Polynomial Models



CONCLUSIONS AND RECOMMENDATIONS

The following are the main conclusion the study.

- The research by Bolukbasi et al. (2014) is verified and confirmed with new data from Illinois. The NBI data need to be filtered to remove the effect of unrecorded rehabilitation or reconstruction work to develop reasonable deterioration curves for bridges.
- The apparent evaluation method is valid for discovering the explanatory relationship between dependent and independent variables. However, it may not suitable for forecasting model selection.
- For the purpose of forecasting ability, external data evaluation with roll-back data is recommended. And the roll-back period should cover the forecasting period to reveal both short- and long-term forecasting power.

This paper proposes and demonstrates an objective, data-based approach for regression model forecasting ability evaluation. If the model is selected based on apparent evaluation only, then the forecasting outcome may not be accurate, especially for long-term planning, maintenance, rehabilitation, and replacement decisions. In this study, both a simple model as polynomial model and a full model selected by the apparent evaluation method have been generated for steel bridge component deterioration that can be used in any MRR decisions with confidence. In addition to producing deterioration curves, the methods described in the paper allow engineers to select the best forecasting model depending on their planning horizon. Finally, it is recommended to expand the use of the proposed procedure to help DOT decision making by developing a performance-based prediction model evaluation criteria.

References

Bolukbasi, Melik, Jamshid Mohammadi, and David Arditi. “Estimating the Future Condition of Highway Bridge Components Using National Bridge Inventory Data.” *ASCE Practice Periodical on Structural Design and Construction* 9, (2004): 16-25.

Clementi, M., S. Clementi, M. Fornaciari, F. Orlandi and B. Romano. “The GOLPE Procedure for Predicting Olive Crop Production from Climatic Parameters.” *Journal of Chemometrics* 15, (2001): 397-404.

Cook, E. and L. Kairiukstis. *Methods of Dendrochronology: Applications in the Environmental Science.* Kluwer Academic Publisher and International Institute for Applied Systems Analysis. Dordrecht, The Netherlands, 1990.

FHWA. *Information Public Disclosure of National Bridge Inventory (NBI) Data, 2007*. [available from: http://www.fhwa.dot.gov/bridge/nbi/20070517.cfm, date accessed: 07-12-2014,]

FHWA. *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation’s Bridges*. Federal Highway Administration, U.S. Department of Transportation, 1995.

Frangopol, D.M., E.S. Gharaibeh, J.S. Kong, and M. Miyake. “Optimal Network Level Bridge Maintenance Planning Based on Minimum Expected Cost.” *Proceedings of the Transportation Research Record*, Florida, (2000): 26–33.

Harrell, F.E., K.L. Lee, and D.B. Mark. “Multivariable Prognostic Models: Issues in Developing Models, Evaluating Assumptions and Adequacy, and Measuring and Reducing Errors.” *Statistics in Medicine* 15, (1996): 361-387.

Lee, Jaeho, K. Sanmugarasa, M.Blumenstein, and Y.C. Loo. “Improving the Reliability of a Bridge Management System (BMS) Using an ANN-Based Backward Prediction Model (BPM).” *Automation in Construction* 17, (2008): 758-772

Lu, Pan, and Denver Tolliver. “Pavement Treatment Short-Term Effectiveness in IRI Change Using Long-Term Pavement Program Data.” *ASCE Journal of Transportation Engineering* 138 (11), (2012): 1297-1302.

McCarthy P.J. “The Use of Balanced Half Sample Replication Cross-Validation Studies.” *Journal of the American Statistical Association* 71, (1976): 596-604.

National Research Council (NCHRP). *NCHRP Synthesis 397: Bridge Management Systems for Transportation Agency Decision Making*. The National Academies Press, Washington, D.C., 2009.

Shao, J. “Linear Model Selection by Cross-Validation.” *Journal of the American Statistics Association* 88, (1993): 486–494.

Snee, R.D. “Validation of Regression Models: Methods and Examples.” *Technometrics* 19, (1977): 415–428.

Steyerberg, E.W. and Frank E. Harrell. “Validation of Predictive Regression Models 2014.” 2014, date accessed: 07-12-2014, www.pitt.edu/~super7/7011-8001/7071.ppt

Tolliver, D., and P. Lu. “Analysis of Bridge Deterioration Rates: A Case Study of the Northern Plains Region.” *Journal of the Transportation Research Forum* 50 (2), (2011): 87-100.

U.S. Department of Transportation (USDOT). *2013 Status of the Nation’s Highways, Bridges, and Transit: Performance Report to Congress*, Washington, D.C., 2014.

Wilks, S. D. *Statistical Methods in the Atmospheric Sciences* (2nd ed.). Academic Press, Elsevier, London, 2006.

Witten, I.H., and E. Frank. *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann Publishers, San Francisco, 1999.

***Pan Lu** is assistant professor of transportation at the Upper Great Plains Transportation Institute at North Dakota State University. She received her Ph.D. in transportation and logistics from North Dakota State University in 2011. Her current research interests include statistical modeling in transportation, asset management, multimode transportation efficiency analysis, transportation system models, operation research in transportation, and transportation safety analysis.*

***Shiling Pei** is assistant professor of civil and environmental engineering at Colorado School of Mines. He received his Ph.D.in civil engineering from Colorado State University in 2007. His current research interests include mechanistic models and non-linear structure dynamics, hazard mitigation and resilient infrastructure system, traditional and innovative timber systems, large scale dynamic testing and monitoring, performance-based engineering, structural reliability, and earthquake induced loss analysis.*

***Denver Tolliver** is director of the Transportation & Logistics program and director of the Upper Great Plains Transportation Institute at North Dakota State University. He is also the director of the five-university Mountain-Plains Consortium, which is one of USDOT's designated university transportation centers. He holds doctoral and master's degrees from the Virginia Polytechnic Institute in environmental design & planning and urban & regional planning, respectively. Since 1989, Tolliver has been awarded $40 million in competitive research grants from federal and state agencies and private industries to conduct highway, railway, waterway, and multimodal analyses.*

The Impact of Driving Knowledge on Motor Vehicle Fatalities

by Walter O. Simmons, Andrew M. Welki, and Thomas J. Zlatoper

This paper analyzes the influence of driving knowledge on highway safety by estimating regression models on U.S. state-level data over six years (2005 through 2010). The models incorporate a representative set of motor vehicle fatality determinants. Driving knowledge—as measured by performance on the GMAC Insurance National Drivers Test—has a statistically significant life-saving effect. Negatively related to the motor vehicle death rate and statistically significant are: real per capita income, precipitation, seat belt use, and a linear trend. Statistically significant positive associations with the rate are found for: the ratio of rural to urban driving, temperature, the percentage of young drivers, the percentage of old drivers, and alcohol consumption.

INTRODUCTION

While trending downward in recent years, annual motor vehicle deaths in the U.S. remain large in number. For example, they totaled 43,510 in 2005 and 32,999 in 2010 (National Highway Traffic Safety Administration [NHTSA] 2013, p. 5). Of interest to policy makers are initiatives that can lead to further declines in roadway fatalities.

Some researchers have suggested that efforts to increase driving knowledge could improve road safety. For example, Amarasingha and Dissanayake (2013) note that education programs that increase awareness of unsafe practices (e.g., failure to yield right of way, driving too fast for conditions) could reduce risk for young drivers. However, the effectiveness of such initiatives requires that increased knowledge results in safer driving.

Does greater driving knowledge contribute to safer highway travel? This paper addresses this question. Specifically, it estimates the relationship between driving knowledge, as measured by performance on the nationally administered GMAC Insurance National Drivers Test, and U.S. motor vehicle fatalities.[1] The estimation controls for the influence of a representative collection of highway death determinants.

This study has the following format: The first section discusses previous research on the determinants of U.S. motor vehicle deaths with a particular focus on the impact of driver education. A model that explains these deaths is specified in the second section. The third section describes the data set used in the analysis. Regression estimates of the model are reported and discussed in the fourth section. The final section summarizes the paper's findings.

BACKGROUND

There has been considerable research on the determinants of U.S. motor vehicle safety. Loeb, Talley and Zlatoper (1994) summarize the collective findings of several selected empirical studies to that point in time. The studies typically use historical data and multivariate statistical techniques (e.g., multiple regression analysis) to estimate the impact of various potential determinants on safety outcome measures (e.g., highway accidents, injuries and fatalities). The determinants can be categorized as economic (e.g., accident cost, income, fuel price, economic activity); driver-related (e.g., alcohol use, speed, gender, age, amount of travel); vehicle-related (e.g., vehicle type, size, mandated vehicle safety features, age); highway-related (e.g., type of roadway, location); environmental (e.g., traffic density, weather, lighting, altitude); and other considerations (e.g., hospital access, geographical area, and time factors).[2] Some studies analyze the effectiveness of deterrent policies (e.g., motor vehicle inspection, minimum legal drinking age, speed limits, seat belt laws).

During the last 20 years, researchers have analyzed the effect of cell phone use on highway safety. Other determinants considered include education levels, crime rates, and suicide rates. In addition to conventional techniques such as multiple linear regression, Bayesian estimation methods have been increasingly utilized. Blattenberger, Fowles, and Loeb (2013) summarize the collective findings of the more recent empirical work.

This body of highway safety research includes efforts to understand how and if drivers' tests and the driver education process affect road safety. Two notable research strands of driver education are the written test and the graduated licensing programs (GDL). Research about the written driving test comprises the early stages of the analysis, while more recent work emphasizes contributory factors and the GDL program. The discussion here follows that order.

One anticipates that a better understanding of the "rules of the road" should create a safer driving environment. Arthur and Doverspike (2001) extended that idea to examine the role of driver personality and its effect on crashes. Their work adds to written driver's test research by Hill and Jamieson (1978); McKnight and Edwards (1982); and Struckman-Johnson and others (1989). Arthur and Doverspike (2001) note that support for driving knowledge as a safety enhancer is equivocal. They, however, find that a driver personality variable, conscientiousness, is negatively related to the number of crashes.

More recent research focuses on changes in the driver education process, more specifically, the experiential portion of young driver development. Over time, all states moved to a GDL process. These activities frame the aspiring driver's road experience prior to acquiring full driving privileges. Each GDL stage works on specific circumstances. The ultimate goal of the driver preparation process is a combination of practical physical experiences and a knowledge of the "rules of the road" that produces a driver less likely to contribute to an unsafe world for the driving public.

Many studies examined the effects of GDL programs on reducing teenage crashes. Typically, each study focused on the experience of a specific state. States analyzed are: Missouri by Bernard and Sweeney (2015); Kansas by Amarasingha and Dissanayake (2013); Maryland, Florida, and Michigan by Ehsani and others (2013); Utah by Hyde and others (2005); and Georgia by Rios and others (2006). The Bernard and Sweeney paper (2015), which examines the contributing circumstances associated with teenage driver fatalities, provides a good list of analyses of this type.

Bernard and Sweeney (2015) use data linking contributory factors to crash fatalities. Contributory factors can then inform the types of changes needed to enhance the effectiveness of GDL programs. While not universal across all state studies, the research results suggest that GDL programs reduced crash rates for teenage drivers.

This paper extends previous work in this area in a number of ways. It revisits the effect of written drivers' tests on road safety. Of particular note is the use of data on a common test collected from drivers across all 50 states. This permits interstate comparison as a standard measure of driving knowledge is utilized.

Additionally, although individual accident data are not used, the state-level (aggregated) data includes variables that control for micro-level causal factors (e.g., alcohol use). The explanatory factors are representative of the types used in the larger body of highway safety research. Embedded within these variables are factors examined in state-specific studies to inform the GDL process.

MODEL

Four categories of explanatory factors are explicitly included in the model: economic conditions, locational factors, weather conditions, and driver characteristics. The model's general form is:

(1) DEATHRT = f(INCOME, RURURB, TEMP, PRECIP, YOUNG, OLD, ALCOHOL, SBELTUSE, KNOWLEDGE)

where	DEATHRT	=	motor vehicle death rate
	INCOME	=	consumer income
	RURURB	=	rural-urban driving mix
	TEMP	=	temperature
	PRECIP	=	precipitation
	YOUNG	=	young drivers
	OLD	=	old drivers
	ALCOHOL	=	alcoholic intoxication while driving
	SBELTUSE	=	seat belt use
	KNOWLEDGE	=	driving knowledge

The expected relationship between each explanatory factor and the death rate is explained below.

Income represents economic conditions. Its impact on highway fatalities is uncertain a priori. Higher income should increase the demand for safety and driving intensity, assuming that both are normal goods.[3] Due to these offsetting considerations, Peltzman (1975) conjectures that the direction of the relationship between income and deaths is unclear. Loeb, Talley, and Zlatoper (1994, pp. 18-19) report that time-series studies provide evidence of a positive relationship, while cross-sectional and pooled analyses indicate a negative association.

Speeds are generally higher during rural travel than during urban travel. As a result, the chance of death is likely greater when an accident occurs in a rural location. Loeb, Talley, and Zlatoper (1994, pp. 32) cite time-series and cross-sectional studies providing statistically significant evidence of inverse associations between motor vehicle fatality measures and the proportion of urban highway travel. Given these findings, the locational measure employed here—the ratio of rural to urban travel—is anticipated to be positively related to the death rate.

Regarding weather conditions, Loeb, Talley, and Zlatoper (1994, p. 34) report that cross-sectional analyses find that temperature and precipitation have statistically significant positive and negative associations, respectively, with highway fatality measures. Higher temperatures may encourage more driving and faster speeds, while more precipitation may foster the opposite. Based on these results, the same associations are expected in this study.

Age is one of the driver characteristics accounted for here. Younger motorists have less experience and are more inclined to take more risks; and older drivers are subject to deterioration in physical factors (e.g., eyesight and reflexes) that influence driving safety. Due to these considerations, younger and older drivers may be more susceptible to motor vehicle accidents and deaths. However, Loeb, Talley, and Zlatoper (1994, pp. 24-25) note that the results in statistical studies on the relationships between these two age groups and death measures are mixed. Given the inconclusive evidence, the anticipated relationship between the extent of driving involvement by the youngest and oldest age groups and highway fatality measures is uncertain a priori.

Alcohol usage is another driver characteristic included in this analysis. According to conventional wisdom, intoxicated drivers are more likely to be involved in fatal crashes. Loeb, Talley, and Zlatoper (1994, pp. 20-21) catalogue research evidence of a significant direct relationship between alcohol consumption and motor vehicle death measures in the U.S. The same association is anticipated in this study.

Another driver characteristic accounted for is seat belt use. According to NHTSA (2001, Exhibit 6) estimates, the manual lap-shoulder belt is highly effective in saving lives of car drivers. In contrast, Garbacz (1990) finds that seat belt use has no statistically significant effect on total or driver or overall occupant (drivers and passengers) deaths, and it has a life-taking impact on non-occupants (pedestrians, cyclists, and motorcyclists) and passengers.[4] Given the mixed evidence, the expected relationship between highway fatality rates and seat belt use is uncertain a priori.

Driving knowledge is represented by performance on the GMAC Insurance National Drivers Test described in the next section. Two state-level performance measures are utilized in this analysis: test average (TESTAVG) and test rank (TESTRANK). Assuming that individuals with greater knowledge drive more safely, motor vehicle death measures are expected to be negatively related to TESTAVG and positively related to TESTRANK.[5]

In addition to the four categories of explanatory factors discussed above, this study controls for spatial and temporal considerations. The former pertains to geographic areas of the U.S., while the latter corresponds to a time trend.

DATA

An online survey to test the knowledge of general driving safety rules among a nationally representative sample of licensed drivers in the U.S. is used in this study. In partnership with TNS (the world's largest custom research agency), General Motors Acceptance Corporation (GMAC) conducted the survey from 2005 to 2011 to determine how many American drivers would meet one of today's basic requirements to obtain a driver's license.[6] The GMAC Insurance National Drivers Test has become the gold standard for America's driving IQ. To test the knowledge of general driving safety rules, participants were administered a 20-question general driving test. The questions were taken from actual written Department of Motor Vehicles (DMV) tests. A balanced sample from the TNS panel, representative of U.S. individuals aged 16-65, was used for the GMAC study. In 2010, a total of 5,130 surveys were completed, with a minimum of 100 surveys per state and Washington, D.C. National data were weighted to percentage of state, age, gender, and ethnicity. National weights were applied when analyzing data on a national level to account for share of voice (i.e., California had a higher percentage in weight value due to the size of its population, while North Dakota was lower). This was only applied when analyzing data on a total level. The study measured at the 95% confidence level. [GMAC Insurance (2011)]

The analysis in this study utilizes annual U.S. state-level data for the years 2005 through 2010. The dependent variable DEATHRT is measured by highway deaths per billion vehicle-miles. The source for the death and vehicle-miles figures is the Federal Highway Administration [FHWA] (various years).

The independent variable INCOME (real per capita disposable income, in dollars) is based on total nominal disposable income values from the Bureau of Economic Analysis (2011), population figures from the U.S. Census Bureau (2011 and 2014), and values of the Consumer Price Index for all urban consumers (base period: 1982-84) [Bureau of Labor Statistics (2014)]. FHWA (various years) is the data source for the explanatory variable RURURB (rural vehicle-miles divided by urban vehicle-miles). Information for the weather variables TEMP (annual mean temperature, in degrees Fahrenheit) and PRECIP (annual precipitation, in inches) comes from the National Climate Data Center (2011).

FHWA (various years) is the data source for the driver characteristics YOUNG (percentage of licensed drivers aged 24 years or younger) and OLD (percentage of licensed drivers aged 65 years or older). Values for ALCOHOL (per capita apparent alcohol consumption, in gallons) for 2005-09 come from the National Institute on Alcohol Abuse and Alcoholism [NIAAA] (2011) and for 2010 come from NIAAA (2014).[7] The sources for information on SBELTUSE (seat belt use rate) for 2005-09 and 2010 are NHTSA (2010) and NHTSA (2011), respectively. Figures for the driving knowledge variables—TESTAVG and TESTRANK—are as reported by GMAC Insurance (2011). TESTAVG is the average percentage score on the GMAC Insurance National Drivers Test for test takers from a particular state. TESTRANK is the numerical position of a particular state's TESTAVG value in a descending-order ranking of all state TESTAVG values.

To account for spatial considerations, dummy variables are included for the nine Census Divisions: New England (NEWENGL), Middle Atlantic (MDATLAN), East North Central (ENOCNTRL), West North Central (WNOCNTRL), South Atlantic (SOATLAN), East South Central (ESOCNTRL), West South Central (WSOCNTRL), Mountain (MOUNTAIN), and Pacific (PACIFIC). The U.S. Census Bureau (2010) is the source for this information. A linear trend variable (TREND) controls for temporal effects. Table 1 provides summary statistics on the variables used in the model estimations.

Table 1: Summary Statistics of Variables

Variable	Mean	Standard Deviation
DEATHRT	13.477	3.907
INCOME	16,118.77	2,105.018
RURURB	0.959	0.789
TEMP	52.864	7.535
PRECIP	37.750	15.102
YOUNG	13.505	1.957
OLD	15.751	1.834
ALCOHOL	2.375	0.470
SBELTUSE	83.150	8.059
TESTAVG	79.592	3.928
TESTRANK	25.196	14.328
NEWENGL	0.122	0.328
MDATLAN	0.063	0.243
ENOCNTRL	0.105	0.307
WNOCNTRL	0.147	0.355
SOATLAN	0.168	0.374
ESOCNTRL	0.084	0.278
WSOCNTRL	0.084	0.278
MOUNTAIN	0.164	0.371
PACIFIC	0.063	0.243
TREND	3.517	1.704

ESTIMATION RESULTS

Table 2 contains the regression estimation results for four different models. In each model the dependent variable is DEATHRT. Models 1 and 2 have linear functional forms, and Models 3 and 4 have log-log specifications.[8] Except for the measures for driving knowledge, the independent variables are the same in all models. In Models 1 and 3, driving knowledge is measured by the state's test average (TESTAVG), while in Models 2 and 4 it is approximated by the state's ranking

Table 2: U.S. State-Level Regression Estimates of Motor Vehicle Deaths per Vehicle-Mile, 2005–2010

Independent Variable	Expected Sign	Dependent Variable: DEATHRT			
		Model 1	Model 2	Model 3	Model 4
Intercept	?	6.463	0.836	3.867[bb]	2.035
		(1.388)	(0.260)	(2.443)	(1.607)
INCOME	?	-3.56E-04[bb]	-3.60E-04[bb]	-0.331[bb]	-0.332[bb]
		(-5.361)	(-5.482)	(-3.638)	(-3.652)
RURURB	+	1.840[aa]	1.901[aa]	0.141[aa]	0.139[aa]
		(9.721)	(10.046)	(9.710)	(9.734)
TEMP	+	0.188[aa]	0.173[aa]	0.852[aa]	0.825[aa]
		(7.747)	(6.906)	(8.941)	(8.467)
PRECIP	-	-0.001	-1.65E-04	-0.061[aa]	-0.059[aa]
		(-0.108)	(-0.013)	(-1.974)	(-1.906)
YOUNG	?	-0.005	0.009	0.118	0.129[b]
		(-0.067)	(0.138)	(1.634)	(1.772)
OLD	?	0.501[bb]	0.507[bb]	0.616[bb]	0.623[bb]
		(7.088)	(7.243)	(8.240)	(8.302)
ALCOHOL	+	1.247[aa]	1.267[aa]	0.226[aa]	0.228[aa]
		(5.004)	(5.131)	(4.887)	(4.931)
SBELTUSE	?	-0.077[bb]	-0.074[bb]	-0.352[bb]	-0.361[bb]
		(-4.871)	(-4.690)	(-3.911)	(-4.021)
TESTAVG	-	-0.057[a]		-0.420[aa]	
		(-1.409)		(-1.808)	
TESTRANK	+		0.029[aa]		0.021[aa]
			(2.707)		(1.890)
MDATLAN	?	3.644[bb]	3.573[bb]	0.225[bb]	0.235[bb]
		(6.960)	(6.904)	(6.200)	(6.583)
ENOCNTRL	?	2.724[bb]	3.027[bb]	0.104[bb]	0.106[bb]
		(5.199)	(5.665)	(3.021)	(3.057)
WNOCNTRL	?	3.306[bb]	3.754[bb]	0.134[bb]	0.142[bb]
		(5.968)	(6.469)	(3.442)	(3.542)
SOATLAN	?	4.460[bb]	4.692[bb]	0.248[bb]	0.252[bb]
		(8.958)	(9.337)	(6.894)	(6.957)
ESOCNTRL	?	5.490[bb]	5.742[bb]	0.288[bb]	0.291[bb]
		(9.381)	(9.739)	(6.655)	(6.711)
WSOCNTRL	?	5.270[bb]	5.620[bb]	0.262[bb]	0.266[bb]
		(8.305	(8.701)	(5.667)	(5.729)
MOUNTAIN	?	6.459[bb]	6.814[bb]	0.355[bb]	0.361[bb]
		(9.510)	(9.907)	(6.765)	(6.792)

(Table 2: continued)

Independent Variable	Expected Sign	Dependent Variable: DEATHRT			
		Model 1	Model 2	Model 3	Model 4
PACIFIC	?	4.662[bb]	5.126[bb]	0.240[bb]	0.256[bb]
		(6.951)	(7.4190)	(5.291)	(5.310)
TREND	?	-0.777[bb]	-0.704[bb]	-0.059[bb]	-0.052[bb]
		(-9.072)	(-11.540)	(-9.761)	(-12.108)
N		286	286	286	286
R^2		0.843	0.846	0.862	0.862
Adjusted R^2		0.833	0.836	0.853	0.853

Notes: t statistics are in parentheses. In Models 3 and 4, all variables except the Census Division dummies and TREND are in natural logarithms. The control category for the Census Divisions is New England (NEWENGL).

[a] significant at .10 level (one-tail test)
[aa] significant at .05 level (one-tail test)
[b] significant at .10 level (two-tail test)
[bb] significant at .05 level (two-tail test)

across all states (TESTRANK). Based on the R^2 statistics reported in Table 2, all four models explain more than 80% of the variation in the motor vehicle death rate.

INCOME is statistically significant and negatively related to DEATHRT in all four models.[9] These results suggest that better economic conditions increase the demand for safety, and fewer fatalities result. This corroborates findings based on pooled cross-section, time-series data as summarized in Loeb, Talley, and Zlatoper (1994, pp. 18-19).

Where a person drives influences DEATHRT. In all four models, there is statistically significant evidence that as the ratio of rural to urban driving increases, so does the fatality rate. Rural driving conditions may involve less congested roads (higher speeds) as well as different types of road conditions. Also, rural settings may offer fewer nearby medical options in the event of an accident and consequently increase the chance of a fatality.

Higher temperatures, and presumably better driving conditions, are positively related to highway fatalities. More precipitation, however, reduces the death rate. Both weather variables may influence the driver's level of attention as well as vehicle speed. The signs for both weather variables are as anticipated, with TEMP significant across all four models and PRECIP statistically related in the log-log models.

The age of the driving population is related to the death rate. A younger driving population generally increases the fatality rate. YOUNG's coefficient is positive in all but Model 1 and is statistically significant in Model 4. There is stronger evidence that older drivers contribute to a higher death rate. The coefficient of OLD is positive and statistically significant in all four models.

Alcohol-impaired motorists create hazardous driving conditions and contribute to motor vehicle fatalities. All four models reveal a statistically significant relationship between alcohol consumption and the death rate. Following conventional wisdom, the estimated coefficients are positive. This aligns with the findings of a large body of previous research on the impact of alcohol on highway safety.

In this analysis seat belt use is found to have a live-saving effect. Across all four models, the coefficient of SBELTUSE is negative and statistically significant. This corroborates previous research findings by NHTSA.

Regardless of the measure used, results suggest that greater knowledge of general highway safety rules enhances highway safety. As expected, the average test score (TESTAVG) coefficients are negative in Models 1 and 3; and the test rank (TESTRANK) coefficients are positive in Models 2 and 4. All of these results are statistically significant.

The control category for the Census Division dummy variables is New England (NEWENGL), so the results for these geographic variables are evaluated in comparison to this omitted division. In all four models, the coefficients for all of the Census Division dummies are positive and statistically significant. This suggests that in the geographic areas included in the estimated models there are factors leading to higher fatality rates than in New England.

The coefficient of TREND is negative and statistically significant in all four models. This implies that there are influences not explicitly controlled for in the estimations that contributed to a decline in the highway death rate over the period analyzed. For example, the trend variable may be capturing improved safety technology built into the driving fleet over time.

SUMMARY AND IMPLICATIONS

This paper is an effort to better understand the factors that influence motor vehicle deaths across U.S. states and over time. One contribution is the addition of driving knowledge, as measured by a written driver's test, to a set of factors consistent with contributory factors to explain deaths per vehicle-mile. Four models, estimated using annual U.S. state-level data over six years (2005 through 2010), provide results generally consistent with previous findings. The estimations use two functional forms: linear and log-log.

Estimation results pertaining to the influences of several explanatory factors are robust across the models that include them. Negatively related to the fatality rate and statistically significant are: real per capita income, precipitation, seat belt use, and a linear trend. The models also reveal statistically significant positive associations with the highway death rate for the ratio of rural to urban driving, temperature, the percentage of young drivers, the percentage of old drivers, and alcohol consumption. Census Division dummy variables add statistically significant explanatory power and reveal death rate differences across geographic regions.

While common perception suggests more knowledge leads to better road safety, earlier empirical support—using a written driver's test as a knowledge measure—was equivocal. This analysis uses two alternative measures of driving knowledge: individual state average and the ranking on the GMAC Insurance National Drivers Test. Data examining all 50 states strongly support the safety effects—as measured by lower death rates—of the written driving test. Regardless of the measure used, driving knowledge exhibits a statistically significant life-saving effect.

A number of implications follow this result. Lack of critical safety comprehension increases the risk of accidents or near accidents. Lowering this risk is likely to reduce both accidents and costs of insurance premiums. Further, increased overall safety is a public good. Finally, greater emphasis on the written test naturally complements the recent emphasis on the GDL programs to produce a better population of novice drivers.

Acknowledgements

An earlier version of this paper was presented at the Eastern Economic Association Meetings in Boston, Massachusetts, on March 8, 2014. The authors thank Dr. Michael W. Babcock, co-general editor, and two anonymous referees for several helpful suggestions and assume responsibility for any remaining errors.

Endnotes

1. Driving knowledge as referred to in this paper focuses on the understanding of driving rules as typically measured by a written driving test.

2. Previous research found that altitude and alcohol consumption have an interactive effect on highway safety. See Loeb, Talley, and Zlatoper (1994, p. 35).

3. According to Peltzman (1975, p. 681), a driver faces a tradeoff between safety and "driving intensity." A reduction in the former (i.e., a higher probability of death from accident) results from an increase in the latter (e.g., greater speed, thrills, etc.).

4. Seat belt use may lead to riskier driving. This may result in harmful consequences for non-occupants.

5. The values for TESTRANK are 1 for the highest ranking state, 2 for the second highest, and so on. Thus, a higher rank corresponds to a lower value on this variable.

6. GMAC Insurance survey data for 2011 are not included in the data set of this study because data for other variables was unavailable.

7. Data on alcoholic intoxication while driving are unavailable. Therefore, information on this activity for the population in general is utilized in this analysis. The assumption is made here that the behavior of drivers with regard to this activity is highly correlated with that in the general population.

8. In Models 3 and 4, all variables except the Census Division dummies and TREND are in natural logarithms.

9. In this paper "statistically significant" refers to significance at a level of .10 or less.

References

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

Arthur, W. Jr., and D. Doverspike. "Predicting Motor Vehicle Crash Involvement from a Personality Measure and a Driving Knowledge Test." *Journal of Prevention & Intervention in the Community* 22(1), (2001): 35-42.

Bernard, J.M., and D.C. Sweeney II. "Contributing Circumstances Impact on Missouri Teenage Driver Crash Fatalities." *Journal of the Transportation Research Forum* 54(1), (2015): 5-21.

Blattenberger, G., R. Fowles, and P.D. Loeb. "Determinants of Motor Vehicle Crash Fatalities Using Bayesian Model Selection Methods." *Research in Transportation Economics* 43, (2013): 112-122.

Ehsani, J.P., C.R. Bingham, and J.T. Shope. "Graduated Driver Licensing for New Drivers: Effects of Three States' Policies on Crash Rates Among Teenagers." *American Journal of Preventive Medicine* 45(1), (2013): 9-18.

Garbacz, Christopher. "Estimating Seat Belt Effectiveness with Seat Belt Usage Data from the Centers for Disease Control." *Economic Letters* 34(1), (1990): 83-88.

GMAC Insurance. *2011 GMAC Insurance National Drivers Test*, 2011. http://www.gmacinsurance.com/SafeDriving/ (accessed March 2014).

Hill, P.S., and B.D. Jamieson. "Driving Offenders and the Defensive Driving Course—An Archival Study." *The Journal of Psychology* 98, (1978): 117-127.

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

Loeb, P.D., W.K. Talley, and T.J. Zlatoper. *Causes and Deterrents of Transportation Accidents: An Analysis by Mode.* Quorum Books, Westport, CT, 1994.

McKnight, A.J., and R. Edwards. "An Experimental Evaluation of Driver License Manuals and Written Tests." *Accident Analysis and Prevention* 14, (1982): 187-192.

National Institute on Alcohol Abuse and Alcoholism, National Institutes of Health. Table 3, "Per Capita Ethanol Consumption for States, Census Regions, and the United States, 1977-2009," 2011. http://pubs.niaaa.nih.gov/publications/Surveillance92/CONS09.htm (accessed January 2014).

National Institute on Alcohol Abuse and Alcoholism, National Institutes of Health. Table 3, "Per Capita Ethanol Consumption for States, Census Regions, and the United States, 1977-2012," 2014. http://pubs.niaaa.nih.gov/publications/surveillance98/CONS12.htm (accessed July 2014).

Peltzman, Sam. "The Effects of Automobile Safety Regulation." *Journal of Political Economy* 83(4), (1975): 677-725.

Rios, A., M. Wald, S.R. Nelson, K.J. Dark, M.E. Price, and A.L. Kellerman. "Impact of Georgia's Teenage and Adult Driver Responsibility Act." *Annals of Emergency Medicine* 47(4), (2006): 369.e1-369.e7.

Struckman-Johnson, D.L., A.K. Lund, A.F. Williams, and D.W. Osborne. "Comparative Effects of Driver Improvement Programs on Crashes and Violations." *Accident Analysis and Prevention* 21, (1989): 203-215.

U.S. Census Bureau. "Annual Estimates of the Resident Population for the United States, Regions, States, and Puerto Rico: April 1, 2000 to July 1, 2009 (NST-EST2009-01)," 2011. http://www.census.gov/popest/data/historical/2000s/vintage_2009/index.html (accessed June 2011).

U.S. Census Bureau. "Geographic Terms and Concepts – Census Divisions and Census Regions," 2010. https://www.census.gov/geo/reference/gtc/gtc_census_divreg.html (accessed July 2014).

U.S. Census Bureau. "2010 Census," 2014. http://www.census.gov/2010census/ (accessed July 2014).

U.S. Department of Commerce, Bureau of Economic Analysis. "SA51-53 Disposable Personal Income Summary," 2011. http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=4#reqid=70&step=30&isuri=1&7028=-1&7040=-1&7083=levels&7031=0&7022=21&7023=0&7024=non-industry&7025=0&7026=01000&7027=2012&7001=421&7029=23&7090=70&7033=-1 (accessed June 2011).

U.S. Department of Commerce, National Climate Data Center. "Climate at a Glance," 2011. http://lwf.ncdc.noaa.gov/oa/climate/research/cag3/cag3.html (accessed June 2011).

U.S. Department of Labor, Bureau of Labor Statistics. "Consumer Price Index – All Urban Consumers," 2014. http://www.bls.gov/ (accessed July 2014).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics Series*. (various years). http://www.fhwa.dot.gov/policy/ohpi/hss/hspubs.cfm (accessed June 2011 for 2005-09 data; accessed July 2014 for 2010 data).

U.S. Department of Transportation, National Highway Traffic Safety Administration. "Fatality Analysis Reporting System/General Estimates System 2011 Data Summary." DOT HS 811 755, 2013. http://www-nrd.nhtsa.dot.gov/Pubs/811755DS.pdf (accessed March 2014).

U.S. Department of Transportation, National Highway Traffic Safety Administration. *Fifth/Sixth Report to Congress: Effectiveness of Occupant Protection Systems and Their Use*. DOT HS 809 442, 2001. http://www-nrd.nhtsa.dot.gov/Pubs/809-442.pdf (accessed March 2014)

U.S. Department of Transportation, National Highway Traffic Safety Administration. "Seat Belt Use in 2009—Use Rates in the States and Territories," *Traffic Safety Facts.* DOT HS 811 324, 2010. http://www-nrd.nhtsa.dot.gov/Pubs/811324.pdf (accessed June 2011).

U.S. Department of Transportation, National Highway Traffic Safety Administration. "Seat Belt Use in 2010—Use Rates in the States and Territories," *Traffic Safety Facts.* DOT HS 811 493, 2011. http://www-nrd.nhtsa.dot.gov/Pubs/811493.pdf (accessed July 2014).

Walter Simmons *is an associate dean and a professor of economics in Boler School of Business at John Carroll University. He received his B.S. in business and economics from Oakwood University in Huntsville, Alabama, and his M.A. and Ph.D. in economics from Wayne State University. His research interests include issues in international financial centers, nonprofit sector, labor market discrimination, economics of health care, and medical malpractice litigation. He has published in a variety of referred journals and has received many distinguished awards.*

Andrew Welki *received his B.A. degree in economics from Wilkes College and his Ph.D. in economics from Penn State University. He started his John Carroll University career in 1982. Since then he has been a four-time recipient of the Wasmer Award for outstanding teaching in the Boler School of Business. In 2005 he received John Carroll's Distinguished Faculty Award. His research interests include sports economics and transportation safety issues, both domestically and internationally. He has published articles in a number of professional journals including the* Atlantic Economic Journal, Managerial and Decision Economics*, and the* Journal of the Transportation Research Forum*. His service as the faculty athletic representative to the NCAA and the Ohio Athletic Conference now exceeds 20 years. Dr. Welki is an avid sports fan and regularly attends a wide range of sporting events for men and women.*

Tom Zlatoper *is a professor of economics in the Department of Economics and Finance at John Carroll University. He received his B.A. in mathematics and economics from Boston College and his M.A. and Ph.D. in economics from Northwestern University. His research interests include transportation safety and sports economics. His work has been published in various scholarly journals including* Journal of Transport Economics and Policy*,* Managerial and Decision Economics*, and* Transportation Research Part E*; and he co-authored the book* Causes and Deterrents of Transportation Accidents: An Analysis by Mode.

Airline Fuel Hedging: Do Hedge Horizon and Contract Maturity Matter?

by Siew Hoon Lim and Peter A. Turner

Large and unpredictable swings in fuel prices create financial uncertainty to airlines. While there are the risks for going unhedged, airlines that hedge to mitigate fuel price risk face the basis risk. This paper examines whether the length of hedge horizon and distance to contract maturity affect the effectiveness of jet fuel cross hedging. Understanding the effects of hedge duration and futures contract maturity helps improve airline's fuel hedging strategies. We find that (1) regardless of the distance to contract maturity, weekly hedge horizon has the highest effectiveness for jet fuel proxies like heating oil, Brent, WTI, and gasoil; (2) heating oil is the best jet fuel proxy for all hedge horizons and contract maturities; and (3) the hedge effectiveness of heating oil is higher for one-month and three-month contracts.

INTRODUCTION

Fuel cost accounts for about one-third of the total operating cost of major passenger airlines in the U.S. (Lim and Hong 2014). Large and unpredictable swings in fuel prices create uncertainty to airlines' financial performance. Like other nonfinancial firms, airlines use financial instruments and contracts to mitigate the impact of fuel price volatility and commodity price risks.

If an airline expects jet fuel price to rise, part of the cost may be shifted toward airfare. But increasing airfare may not be possible given the current market structure in the U.S. passenger airline industry. Airlines instead are able to use financial contracts that have petroleum products as underlying assets, even though airlines do not actually consume any of the underlying assets. Airlines can set up hedges when the underlying asset is highly correlated with jet fuel. However, these cross hedges carry extra risk with them, and the correlation may not be strong during the duration of the futures contract. Along with the basis risk[1] that a futures contract carries, the change in the correlation between the two assets could cost an airline greatly (Turner and Lim 2015).

In addition to forward contracts[2], airlines' fuel hedging programs also rely on futures contracts traded on the New York Mercantile Exchange (NYMEX) or the Intercontinental Exchange (ICE). The futures contracts commonly used by airlines include U.S. West Texas Intermediate crude oil (WTI), heating oil, traded on the NYMEX, as well as Brent crude oil (Brent) in Europe and gasoil traded on the ICE. Forward contracts are often utilized in the absence of an established exchange for jet kerosene. Derivatives like swaps, options, and collars (which are combinations of swaps and options) are also used.[3]

Southwest Airlines (Southwest) is regarded as a relatively experienced hedger in the industry. The company uses financial instruments or hedging contracts to decrease "its exposure to jet fuel price volatility" (Southwest 2012, page 99). However, despite its impressive net gains of $1.3 billion from fuel derivative contracts' settlements in 2008 (while other airlines experienced losses), Southwest recognized net losses of $64 million and $157 million in fuel hedging in 2011 and 2012, respectively (Southwest 2013). The airline reckoned that "ineffectiveness is inherent in hedging jet fuel with derivative positions based in other crude oil related commodities, especially given the past volatility in the prices of refined products" (Southwest 2015, page 25).

Irish budget airline Ryanair reported a 30% increase in fuel cost in the 2012 fiscal year despite, and because of, its fuel hedging programs covering as high as 90% of its quarterly fuel requirements. Jet fuel accounted for 45% of Ryanair's operating costs in 2013, up from 43% in 2012 and 39% in

2011.[4] The company's low fares and no-fuel-surcharges policy further limit its ability to pass on the fuel costs to passengers. One of its U.S. counterparts, Allegiant, does not hedge. Other U.S. airlines have tried hedging but ceased later on, like US Airways that ceased hedging after 2008. American Airlines, following its merger with US Airways, will terminate its fuel hedging program and allow all outstanding contracts to run off.

Corley (2013) of Mercatus Energy Advisors wrote, "The vast majority of fuel hedging mistakes are the result of a poor or non-existent hedging policy, or a failure to abide by the policy. Most hedging mistakes can be avoided if the company takes the time and effort to create a proper hedging policy." On the other hand, an airline that chooses not to hedge faces the risk of jet fuel price swings. Due to shifts in demand and production the price of the jet fuel differential can easily change considerably in a year (Halls 2005). This added risk of the jet fuel differential means that airlines have to hedge with an asset that is highly correlated with jet fuel.

Recent studies on this issue have focused on identifying a suitable commodity for jet fuel cross hedging (Adams and Gerner 2012), the effect of fuel hedging on annual operating costs and efficiency (Lim and Hong 2014), and a study by Rampini et al. (2014) who find that U.S. airlines with increasing financial constraints or have low net worth are likely to hedge less due to the decreased financial ability to hedge. Thus, if an airline chooses to hedge its fuel costs, it must be financially capable and willing to bear risks. Still there is no guarantee that hedging will generate desirable outcomes for airlines, and hedging may also expose firms to considerable basis risk resulting from factors beyond the firm's control.

Moreover, despite being the major consumers of jet fuel, the ability of airlines to influence oil prices is very limited, if not null (Morrell and Swan 2006). Making hedging even harder, much of the variance in oil pricing is sudden and sharp changes, making interpretation of the changes difficult (Gronwald 2012). Samuelson (1965) suggests that futures prices become more volatile as the time to expiration nears, but the proposition does not always hold (Brooks 2012). Besides the effect of maturity, the effectiveness of a hedge also hinges on the hedge horizon or the holding period (Chen et al. 2003).

Thus, understanding the effects of hedge duration and futures contract maturity helps improve airline strategies for cross hedging jet fuel. In this paper, we examine whether the length of hedging period and the distance to contract maturity affect the effectiveness of jet fuel cross hedging. A number of studies have attempted to address the effects of hedging horizon and contract maturity, few tried to address both simultaneously, but none tried to address both for jet fuel cross hedging. This study seeks to answer the question "Do futures contracts' holding period (or the hedge horizon) and the time to maturity influence the effectiveness of airlines' jet fuel cross hedging?" To answer this question, we examine the hedging performance of four common jet fuel proxies (WTI, Brent, heating oil and gasoil) with different futures contract maturities and holding periods. The results will enable airlines to identify a suitable cross hedge proxy and an optimal hedging strategy that minimizes jet fuel hedging risk and maximizes hedge effectiveness, which in turn stabilizes costs and reduces earning volatility.

LITERATURE REVIEW

Fuel Price Risk and the Airline Industry

Commodity price risk deals with the uncertainty in the future price of a good in the market. The commodity markets tend to be more sensitive to price changes, leading both financial and nonfinancial firms to enter into derivative contracts. Commodity price risk is the largest risk for airlines. Even with the increased efficiency of airplanes, jet fuel can still be over 30% of an airline's operating cost. There is much literature that exists on this subject and the majority is connected with how hedging affects airlines. The reason for this debate is that while there are the risks for changes in the price, airlines that use fuel hedging to control commodity price risk do not always have lower operating expenses (Lim and Hong 2014).

After the success of Southwest Airlines' fuel hedge in the early 2000s, many other passenger airlines have started to hedge their fuel costs. However, Halls (2005) states that a fuel hedge is not as straightforward as it may seem. One such problem is that for fuel hedging, the actual asset is not associated with a widely traded derivative. This means there will have to be some cross price hedging, where the firm hedges a different commodity to the one it actually uses, but figures that the price will correlate to the commodity it uses. For fuel there are many options from Brent, WTI, heating oil, and gasoil.[5] These products are closely related to jet fuel, but that does not mean all of them are ideal for cross hedging. As Halls (2005) mentions anecdotally, while some firms used heating oil, there could be great losses in those hedges because at times heating oil and jet fuel did not track each other at all. But even with that, on a simple regression he found that over a period of two years heating oil was around 90% correlated and crude was about 80%.

Nevertheless, even with this information, there are still unknown variables that could cause the correlation to change, like a change in the cost of the jet fuel differential. The differential is a premium for further refining of the fuel that is needed; however, it can change by large amounts for seemingly unknown reasons. If WTI crude is used to hedge jet fuel exposure, it most likely will not follow jet fuel exactly. This difference in relationship is part of hedge effectiveness, but it also is considered to be part of the basis risk.

The Effects of Duration and Maturity on Hedging Performance

Airlines may hedge for various reasons. In practice, however, hedging may also expose firms to considerable basis risk resulting from factors beyond a firm's control during the course of a hedge. The relationship of hedge effectiveness with hedge duration (or holding period) and contract maturity has been extensively examined by Ederington (1979), Malliaris and Urrutia (1991), Lindahl (1992), Holmes (1996), Chen et al. (2003), Ripple and Moosa (2007), and Adams and Gerner (2012), among others.

Ederington (1979) finds that longer durations are associated with better hedging performance for futures contracts for T-Bill and GNMA 8% pass-through certificates. Lindahl (1992) finds that hedge ratios[6] increase with hedge duration for stock futures. Holmes (1996) explains that due to arbitrageurs' activities, differences between spot and futures would not be large; this means that fractions of the total risk decreases as the duration of hedge increases. He finds the effectiveness of the FTSE-100 stock index futures for stock portfolios is higher for longer duration hedges. Malliaris and Urrutia (1991) find that for foreign currency hedging, relative to a one-week hedge duration, a one-month holding period is associated with a higher R^2 in the OLS regression, but the portfolio return would be higher with a one-week holding period.

Looking into futures contracts for 25 different commodities, Chen et al. (2003) examine the relationship between the hedge ratio and the hedge duration. They find that most of the hedge ratios are below one and increase with the hedge duration, and that hedge effectiveness rises with increased hedge duration.

For WTI futures, Ripple and Moosa (2007) find that the hedge ratio, derived from the slope coefficient in a simple regression, is lower for futures contracts closer to maturity; additionally, they also find that WTI futures contracts with a near-month maturity are more effective than those with a six-month maturity. This observation is consistent with Samuelson's hypothesis (1965) which argues that futures prices are less volatile than spot prices and the futures price volatility decreases when the time to maturity increases. Ripple and Moosa (2007) also observe that the hedge ratios are greater than one in some cases; the reason for this is that the hedge ratio is expected to be less than one for near-maturity contracts, and if the futures price is as volatile or more than the spot price, then the hedge ratio should not be greater than one (Cecchetti et al. 1988). But if the futures price is less volatile than the spot price, it is possible for the hedge ratio to exceed one.

However, Ripple and Moosa (2007) did not attempt to assess the suitability of petroleum proxies for jet fuel. Adams and Gerner (2012) use forward contracts with different maturities used for jet fuel cross hedging to determine the value at risk as well as the hedge effectiveness, which is measured by the model's log-likelihood value and the coefficient of the error correction term. They find that optimal cross hedging instruments are dependent upon the maturity of the instrument's forward contract, and that optimality decreases with increased time to contract maturity. The optimality of a hedge is defined by a hedging strategy that yields the minimum variance hedge ratio, hence the least variability in returns. Their results show that a gasoil forward with maturities of three months or less is the best cross hedge instrument for jet fuel; but WTI and Brent forwards with maturities longer than three months are more superior than gasoil for jet fuel cross hedge. Since Adams and Gerner (2012) used forward contracts, the study did not examine the effect of the holding period on hedge effectiveness. A recent study by Turner and Lim (2015) examined the effectiveness of WTI, Brent, gasoil, and heating oil for jet fuel using daily data, but the study assumed a one-day holding period and did not examine the effect of hedge horizon on hedge effectiveness. Neither of the studies by Adams and Gerner (2012) and Turner and Lim (2015) examined the relationship between the hedge horizon and the hedge effectiveness of jet fuel cross hedging.

Hedge effectiveness is paramount. If a firm's hedges do not meet the requirement for hedge effectiveness, then hedge accounting rules do not apply, and the gains and losses from the firm's derivatives must be recognized in the quarterly financial statement, and thereby exacerbating earning volatility (Zhang 2009). In the United States, the hedge accounting standard (the Statement of Financial Accounting Standards No. 133, or SFAS 133) was initiated by the U.S. Financial Accounting Standards Board (FASB) in 1998.

A hedge is considered highly effective if the changes in fair value or cash flow of the hedged item and the derivative instrument offset each other. While the SFAS 133 does not make any numeric definition, the rule-of-thumb is a correlation coefficient of 0.90 or an adjusted R^2 of 0.80 or higher, in which case the hedge is deemed highly effective. The *ex ante* effectiveness of a hedge must be evident before implementing the hedge, and the hedge must continue to be evaluated for effectiveness on an *ex post* basis throughout the life of the hedge (Finnerty and Grant 2002; CME Group 2012).

Airlines commonly use the regression method to determine if a hedge is effective. Nevertheless, owing to high oil price volatility, hedge ineffectiveness is rather common for the airline industry. For example, Southwest lost hedge accounting for all its unleaded gasoline derivative instruments and certain types of commodities used in hedging (Southwest Airlines 2012).

ECONOMETRIC MODELS

Johnson (1960) shows that the optimal hedge ratio for a portfolio may be derived from minimizing the variance of the portfolio returns. The underlying assumption of the minimum variance principle is that hedgers are risk averse and are therefore involved in hedging to reduce risk. Airlines must choose a fraction of jet fuel spot positions that needs to be offset by opposition positions on futures markets.

Now let S_t and F_t be respectively the logarithms of the spot and futures prices; let ΔS_t be the log difference of spot prices, $\Delta S_t = S_t - S_{t-1}$, and ΔF_t be the log difference of futures prices, $\Delta F_t = F_t - F_{t-1}$. We consider the returns of a portfolio to an airline with a long cash position and a short futures position:[7]

(1) $R_t = \Delta S_t - \beta \Delta F_t$,

where β is the hedge ratio, which is the quantity of a futures asset bought relative to the quantity of a spot asset, like jet fuel. The firm takes out opposite positions in the spot and futures markets to enable itself to offset losses incurred in one market with gains from the other market.

Since hedgers are concerned with the portfolio returns from the beginning to the end of the holding period, according to Chen et al. (2003), the differencing interval in equation (1) should be the hedge duration or the holding period of the futures contract. This implies that the differencing interval should be one week for a one-week holding period, and weekly data should be used. In other words, since the differencing interval is based on the data frequency, the data frequency is the hedge duration. Thus, the value of a portfolio with a k-period hedge duration involves k-period differencing, and equation (1) may be rewritten as:

(2) $R_t = \Delta_k S_t - \beta \Delta_k F_t$,

Where $\Delta_k S_t = S_t - S_{t-k}$ and $\Delta_k F_t = F_t - F_{t-k}$. If $k = 1$, then equations (1) and (2) are identical.

In the simplest case, the minimum variance hedge ratio is assumed to be constant and can be obtained by means of a simple linear regression model (Ederington 1979) estimated by the ordinary least squares approach. For a given one-period hedge duration, the cross hedge model is specified as:

(3) $\Delta S_t = \alpha + \beta \Delta_k F_t + \varepsilon_t$

Where β is the minimum variance hedge ratio which measures the effectiveness of the cross hedge. The OLS estimator $\hat{\beta}$ produces the smallest variance in the returns of a portfolio. Equation (3) is appealing given its simplicity, but a number of issues arise with it.

The first is that the hedge ratio derived by (3) is time-invariant regardless of changes in price information in the spot and futures markets. Hedgers take opposite positions in futures and spot markets so that any losses incurred in one market could be at least partially offset by gains in the other market. For example, if an airline's exposure was one million gallons of jet fuel, it could choose to cross hedge this exposure with NYMEX heating oil futures contracts. The trading unit for heating oil futures at NYMEX is 1,000 barrels (or 42,000 gallons). The minimum variance hedge ratio in equation (3) is a constant value. If the ratio is 0.8, then the number of heating oil futures contracts that the airline should hold is $\frac{0.8 \times 1{,}000{,}000}{42{,}000} = \mathbf{19.05}$, or 19, which is 19,000 barrels of heating oil.

Although the hedge ratio in equation (3) yields a constant, minimum variance in the value of the hedged position, Cecchetti et al. (1988) argue and Myers (1991) and Baillie and Myers (1991) show that the optimal hedge ratios for a portfolio may be time-varying as new information becomes available and market participants adjust their positions. To address this issue, past studies have applied multivariate generalized autoregressive conditionally heteroskedastic (GARCH) models to describe the spot-futures relationship as well as their distributions. A multivariate GARCH model allows time-varying optimal hedge ratios to be estimated from the covariance matrix.

A second problem with respect to equation (3) is that the model specification disregards the possible long-term equilibrium relationship between the spot prices of jet fuel and the futures prices of another petroleum commodity (Adams and Gerner 2012). If so, they are known to be cointegrated, and a certain linear combination of these series is stationary. If a pair of data series are cointegrated, the first differences of the two series can be modeled using a vector autogression model with an error correction term. The resulting model is a vector error correction model (VECM).

To address these two issues, we apply multivariate GARCH models with error correction terms. By allowing the whole covariance matrix to vary through time, multivariate GARCH models may be used to estimate the conditional volatilities of a set of time series variables while permitting the contemporaneous shocks to variables to be correlated with each other since shocks that affect one variable could also affect the other variables. The analysis in this paper uses bivariate GARCH models of the joint distribution of the jet fuel spot price and the futures price for each of the four oil commodities.

The time-varying (or dynamic) optimal hedge ratio can be obtained by the ratio of the conditional covariance between S_t and F_t to the conditional variance of F_t (Kroner and Sultan 1993):

(4) $$\beta_t^* = \frac{cov(S_t, F_t)}{var(F_t)}.$$

The optimal hedge ratio in (4) depends on the covariance of S_t and F_t and the variance of F_t at time *t*. If both the covariance and variance terms are constant, the hedge ratio may be derived using OLS. To account for new information, we specify a model in which the spot and futures prices are specified in a Bollerslev's (1990) constant conditional correlation (CCC) model and with error correction:

(5) $$\begin{aligned} S_t &= \alpha_0 + \alpha_1(S_{t-1} - \gamma_0 - \gamma_1 F_{t-1}) + \varepsilon_{S,t} \\ F_t &= \beta_0 + \beta_1(S_{t-1} - \gamma_0 - \gamma_1 F_{t-1}) + \varepsilon_{F,t}, \\ &\begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix} |\Psi_{t-1} \sim tdist(0, \mathbf{H}_t) \end{aligned}$$

(6) $$\begin{aligned} \mathbf{H}_t &= \begin{bmatrix} h_{SS,t} & h_{SF,t} \\ h_{FS,t} & h_{FF,t} \end{bmatrix} = \begin{bmatrix} h_{S,t} & 0 \\ 0 & h_{F,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} h_{S,t} & 0 \\ 0 & h_{F,t} \end{bmatrix} \\ h_{SS,t} &= c_1 + a_1 \varepsilon_{t-1}^2 + b_1 h_{SS,t-1} \\ h_{FF,t} &= c_2 + a_2 \varepsilon_{t-1}^2 + b_2 h_{FF,t-1}, \end{aligned}$$

where $(S_{t-1} - \gamma_0 - \gamma_1 F_{t-1})$ in (5) is the error correction term, Ψ_{t-1} is the information at time t–1; the residuals, ε_t, follow a bivariate t distribution with zero mean and a conditional covariance matrix, $\mathbf{H}_t$. In (6), $h_{SF,t}$ is restricted to be a constant, and the correlation, ρ is not a function of time. The assumption of a constant correlation may be restrictive. Hence, we consider two additional model specifications below.

An alternative to the CCC GARCH is the BEKK specification, which converts the covariance matrix to be a vector of variances and covariances. We consider the diagonal BEKK specification[8] by Engle and Kroner (1995). For a bivariate GARCH(1,1), the diagonal BEKK is given by

(7) $$\begin{aligned} \mathbf{H}_t = \begin{bmatrix} h_{SS,t} & h_{SF,t} \\ h_{FS,t} & h_{FF,t} \end{bmatrix} &= \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \\ &+ \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \begin{bmatrix} h_{SS,t-1} & h_{SF,t-1} \\ h_{FS,t-1} & h_{FF,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}, \end{aligned}$$

and plainly,

(8) $$\begin{aligned} h_{SS,t} &= c_{11} + a_{11}^2 \varepsilon_{S,t-1}^2 + b_{11}^2 h_{SS,t-1} \\ h_{FF,t} &= c_{22} + a_{22}^2 \varepsilon_{F,t-1}^2 + b_{22}^2 h_{FF,t-1} \\ h_{SF,t} &= c_{12} + a_{11} a_{22} \varepsilon_{S,t-1} \varepsilon_{F,t-1} + b_{11} b_{22} h_{SF,t-1}. \end{aligned}$$

In (8), each of the conditional variances, $h_{SS,t}$ and $h_{FF,t}$, depends on its lagged term and the square of the lagged error terms. Thus, a shock at time *t* will affect ε_t and will affect h_{SS}, h_{FF} and h_{SF} in the next period.

The diagonal BEKK is an alternative form of the diagonal VECH GARCH and has advantage of the VECH, because the BEKK specification guarantees the covariance matrix to be positive semi-definite (Bauwens et al. 2006), and as long as $a_{ii}^2 + b_{ii}^2 < 1 \; \forall \; i$, the BEKK is guaranteed to be stationary (Ledoit et al. 2003).

Based on equation (4), the dynamic hedge ratios may be derived from the bivariate CCC and BEKK GARCH models, and they are given by

(9) $\hat{\beta}_t^* = \frac{\hat{h}_{SF,t}}{\hat{h}_{F,t}}$,

where $\hat{h}_{SF,t}$ is the estimated conditional covariance, and $\hat{h}_{F,t}$ is the estimated conditional variance.

The hedge ratio in (9) targets returns volatility minimization, so it yields the smallest variance of portfolio returns, $Var(R_t^*)$. Following Ederington (1979), we compare the variance of a hedging portfolio to an unhedged portfolio to evaluate the effectiveness of a cross hedge. Specifically, hedge effectiveness is measured by:

(10) $HE = 1 - \frac{Var(\Delta S_t - \hat{\beta}_t^* \Delta F_t)}{Var(\Delta S_t)}$,

where $Var(\Delta S_t - \hat{\beta}_t^* \Delta F_t) = Var(R_t^*)$ is the smallest variance of the returns to a hedged portfolio, and $Var(\Delta S_t)$ is the variance of the returns to an unhedged portfolio. The ratio of the two variances shows the relative volatility in returns; subtracting the ratio from one yields the percentage of volatility reduction derived from a hedged portfolio over an unhedged portfolio.

DATA

The time span of this analysis is from April 15, 1994, through February 27, 2014. The jet fuel spot is the U.S. Gulf Coast 54 jet fuel spot price. This spot market was chosen because it is the most active among the six jet fuel markets in the U.S. (Argus 2012). We consider four usual cross hedge proxies for jet fuel: WTI sweet crude, its European crude oil counterpart North Sea Brent (Brent), No. 2 heating oil traded as New York Harbor ultra-low sulfur No. 2 diesel, and gasoil traded in Europe. WTI and No. 2 heating oil are traded on the New York Mercantile Exchange (NYMEX). Brent and gasoil are traded on the Intercontinental Exchange (ICE). The futures price data were obtained with 3, 6, 9, and 12 month rolling contracts for each commodity. These strips of months were designed to provide a rolling price for contracts expiring 3, 6, 9, or 12 months in the future.[9]

The spot and futures prices are daily data retrieved from the Bloomberg Professional Service. Since we would like to examine the hedge duration on hedging performance, and assuming that portfolio adjustments are made on daily, weekly and monthly bases, we must first construct the appropriate data series for our analysis. The hedge durations considered in this study are one day, one week, and four weeks (1 month). Obviously, the daily data can be applied for one-day hedge duration, and the sample size is 4,985 observations. For weekly hedge horizon, we construct the weekly price series using Wednesday-to-Wednesday's closing prices, as in Myers (1991) and Park and Switzer (1995). If there is no trading on Wednesday due to a public holiday, then the closing price on Tuesday is used. The resulting sample size is 1,032 weekly observations from April 18, 1994, to February 24, 2014. Monthly price series are constructed with four-week data, and an overlapping window is used as in Malliaris and Urrutia (1991). The sample size for the monthly frequency data is 1,028.

We conduct the augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test to test for nonstationarity in the price data. We use Schwarz Information Criterion (SIC) to determine the appropriate number of lags. Based on the test results, the log level price series are nonstationary. Table 1 displays the summary statistics for spot and futures prices as well as the results of the KPSS test for stationarity.[10] The standard deviations of jet fuel spot price differences are higher than those for the futures prices, suggesting more volatility in the spot market. The standard deviations of futures price differences get smaller as the time to maturity increases; this is in line with Samuelson's (1965) proposition about the relative volatility of spot and futures prices, and futures prices approaching contract maturity tend to move closely with the spot prices.

We also conduct the Engle-Granger cointegration test on $u_t = S_t - \gamma_0 - \gamma_1 F_t$. Results from the ADF and PP tests on u_t conclude that u_t is stationary, implying the presence of a long-run equilibrium relationship between the spot price and each of the commodity's futures price series. Thus, the error correction term $u_{t-1} = S_{t-1} - \gamma_0 - \gamma_1 F_{t-1}$ is included as an additional regressor in the two conditional mean equations in the form of a vector error correction model (VECM) with GARCH errors.

EMPIRICAL RESULTS

For each hedge horizon or holding period, we estimate the spot and futures prices for each of the four commodities for each of the five maturities for the entire sample period. We present the conventional hedge ratios that we estimated from all the OLS regressions in Table 2. We observe some patterns in the results. Firstly, based on the constant hedge ratio derived from the OLS regression in equation (3), all adjusted R^2's fall below 80%, suggesting that none of the oil commodities used for cross hedging jet fuel satisfies the conventional threshold for high hedge effectiveness in the constant hedge ratio portfolio.

Secondly, based on the adjusted R^2's, heating oil appears to be more suitable for cross hedging jet fuel for all maturities (one to 12 months) and for all hedge horizons (daily, weekly, and monthly). Thirdly, heating oil contracts maturing in one month have the highest effectiveness, but the effectiveness decreases with distance of maturity. For Brent and gasoil, the hedge effectiveness is higher with the three-month maturity. In most cases, the hedge ratios rise and exceed one with distance to maturity. That is, the longer the distance to maturity, the higher the hedge ratio. Overall, the characteristics of the hedge ratio and the distance to maturity are largely consistent with the findings by Ripple and Moosa (2007) who observe higher hedge ratios (or ratios greater than one in some cases) for longer maturity contracts.

Next, the weekly hedge horizon appears to be more effective for all commodities. As shown by the estimated values of β in Table 2, gasoil performs poorly as a jet fuel proxy for a one-day or a one-month horizon. For a one-week horizon, however, the effectiveness of gasoil contracts maturing in one or three months is the second most desirable after heating oil contracts.

The conventional hedge ratio estimated via OLS regression imposes the restriction that the hedge ratio is time-invariant and does not respond to new information or shocks. Based on the Lagrange multiplier test (not reported), the residuals in all the OLS models for all commodities exhibit the ARCH effects, implying the presence of time-varying variances. We apply the Engle-Granger cointegration test for each commodity to test for the long-run equilibrium relationship between the energy commodity and jet fuel. The test results confirm the existence of such a long-run relationship. Thus, the GARCH (1,1) specification with error correction is found to be an adequate representation of the volatilities in spot and futures prices for all data frequencies. Additionally, the distribution of the OLS residuals is found to be leptokurtic; to account for excess kurtosis,[11] the residuals in the GARCH models are assumed to follow the Student's *t* distribution. The GARCH results for the WTI futures contracts one month to maturity with a one-day hedge horizon is reported in Table 3.

Table 1: Summary Statistics and Stationarity Test Results†

	Daily: Log Level			1st Daily Difference			Weekly: Log Level			1st Weekly Difference			4th Weekly Difference		
	Mean	**S.D.**	**KPSS**	**Mean**	**S.D.**	**KPSS**	**Mean**	**S.D.**	**KPSS**	**Mean**	**S.D.**	**KPSS**	**Mean**	**S.D.**	**KPSS**
Jet Fuel															
Spot	4.7453	0.7143	0.469***	0.0004	0.0246	0.035	4.7455	0.7155	3.706***	0.0018	0.0515	0.034	-0.0002	0.2273	0.010
WTI															
1-month	3.7076	0.6707	0.468***	0.0004	0.0234	0.032	3.7073	0.6718	3.556***	0.0021	0.0475	0.034	-0.0001	0.2142	0.024
3-month	3.7070	0.6792	0.541***	0.0004	0.0197	0.040	3.7069	0.6802	3.783***	0.0021	0.0413	0.038	0.0000	0.1885	0.002
6-month	3.6996	0.6885	0.617***	0.0004	0.0175	0.055	3.6997	0.6893	3.809***	0.0021	0.0363	0.047	0.0000	0.1670	0.003
9-month	3.6910	0.6948	0.685***	0.0004	0.0163	0.070	3.6914	0.6955	3.817***	0.0021	0.0335	0.057	0.0000	0.1545	0.005
12-month	3.6833	0.6992	0.741***	0.0003	0.0154	0.087	3.6839	0.6998	3.818***	0.0021	0.0314	0.070	0.0000	0.1452	0.005
Brent															
1-month	3.6918	0.7325	0.836***	0.0004	0.0215	0.032	3.6915	0.7339	3.775***	0.0019	0.0446	0.035	0.0000	0.2059	0.012
3-month	3.6881	0.7373	0.844***	0.0004	0.0190	0.035	3.6882	0.7382	3.808***	0.0019	0.0397	0.039	0.0000	0.1822	0.010
6-month	3.6802	0.7438	0.877***	0.0004	0.0171	0.040	3.6806	0.7446	3.833***	0.0019	0.0356	0.048	0.0000	0.1643	0.007
9-month	3.6719	0.7487	0.899***	0.0004	0.0160	0.044	3.6725	0.7494	3.843***	0.0019	0.0329	0.058	0.0000	0.1531	0.002
12-month	3.6640	0.7524	0.934***	0.0004	0.0153	0.048	3.6647	0.7529	3.847***	0.0019	0.0312	0.068	0.0000	0.1455	0.001
Gasoil															
1-month	5.8635	0.7223	0.508***	0.0004	0.0201	0.046	5.8633	0.7232	3.718***	0.0018	0.0437	0.044	0.0000	0.1930	0.000
3-month	5.8634	0.7214	0.553***	0.0004	0.0180	0.055	5.8635	0.7223	3.749***	0.0018	0.0389	0.048	0.0000	0.1711	0.014
6-month	5.8635	0.7222	0.642***	0.0004	0.0159	0.073	5.8639	0.7229	3.774***	0.0017	0.0343	0.060	0.0000	0.1515	0.017
9-month	5.8608	0.7249	0.721***	0.0004	0.0148	0.090	5.8616	0.7254	3.788***	0.0017	0.0313	0.076	0.0000	0.1391	0.019
11-month	5.8584	0.7269	0.764***	0.0004	0.0144	0.100	5.8593	0.7272	3.793***	0.0017	0.0298	0.083	0.0000	0.1330	0.021
Heating Oil															
1-month	4.7367	0.7086	0.472***	0.0004	0.0225	0.039	4.7372	0.7097	3.731***	0.0019	0.0460	0.040	0.0000	0.2070	0.006
3-month	4.7400	0.7101	0.531***	0.0004	0.0193	0.047	4.7407	0.7111	3.761***	0.0018	0.0402	0.043	0.0000	0.1789	0.003
6-month	4.7392	0.7126	0.613***	0.0004	0.0172	0.062	4.7399	0.7134	3.788***	0.0018	0.0355	0.051	0.0000	0.1584	0.001
9-month	4.7347	0.7160	0.696***	0.0003	0.0159	0.080	4.7358	0.7166	3.805***	0.0017	0.0318	0.070	0.0000	0.1435	0.019
12-month	4.7299	0.7191	0.762***	0.0004	0.0152	0.093	4.7313	0.7196	3.815***	0.0017	0.0298	0.082	0.0000	0.1366	0.007
#obs		4985			4984			1032			1031			1028	

†KPSS test results: *** indicates rejecting the null hypothesis of stationarity at the 1% significance level

Table 2: Conventional Hedge Ratios by Maturity and Hedge Horizon†

	Hedge Horizons					
	Daily		Weekly		Monthly	
WTI	β	Adj. R^2	β	Adj. R^2	β	Adj. R^2
1-month	0.72703	0.47535	0.75443	0.48442	0.68538	0.41689
3-month	0.92276	0.54613	0.91542	0.53999	0.85126	0.49815
6-month	1.02271	0.53283	1.03257	0.52984	0.96340	0.50053
9-month	1.08394	0.51205	1.10312	0.51396	1.03199	0.49207
12-month	1.11992	0.49077	1.15118	0.49361	1.08433	0.47939
Brent						
1-month	0.80740	0.49367	0.84331	0.53306	0.78279	0.50263
3-month	0.94280	0.53060	0.96722	0.55576	0.90956	0.53130
6-month	1.03591	0.51662	1.06580	0.54193	1.00198	0.52401
9-month	1.07547	0.48784	1.13293	0.52532	1.06847	0.51744
12-month	1.09493	0.46188	1.16711	0.49927	1.10787	0.50269
Gasoil						
1-month	0.66587	0.29441	0.87914	0.55666	0.81348	0.47679
3-month	0.78936	0.33065	0.99184	0.56130	0.92121	0.48061
6-month	0.85694	0.30668	1.08686	0.52487	1.01019	0.45278
9-month	0.89733	0.28971	1.15139	0.48863	1.07500	0.43230
11-month	0.90562	0.27800	1.18905	0.47295	1.11453	0.42491
Heating Oil						
1-month	0.89632	0.66679	0.94618	0.71545	0.92670	0.71254
3-month	1.04084	0.66551	1.06112	0.68660	1.04445	0.67595
6-month	1.12381	0.61527	1.13844	0.61619	1.12181	0.61106
9-month	1.19221	0.58873	1.23237	0.58078	1.21322	0.58635
12-month	1.22159	0.56925	1.31062	0.57502	1.28094	0.59203
#obs	4984		1031		1028	

† The cross hedge model is given in equation (3) and estimated by OLS.

In Table 3, all the coefficients are statistically significant, implying that a GARCH specification is appropriate. For each commodity and model, the *t* distribution degrees of freedom parameter is statistically significant, indicating that the standardized errors are not normally distributed. High persistence in volatility is observed in each model in Table 3, where $a_{ii}^2 + b_{ii}^2$ and $a_i + b_i$ are close to 1 for the BEKK and the CCC models, respectively. Also, in the CCC models, the constant correlation, ρ, between jet fuel and heating oil is the highest at 0.924, and the correlation between jet fuel and gasoil is 0.595, which is the lowest of the four.

The dynamic hedge ratios, $\hat{\beta}_t^*$, in equation (9) can be estimated from the second moments, which are given by equations (6) and (8). We then estimate the portfolio returns R_t in equation (2) using the value of $\hat{\beta}_t^*$ for each day. Since $\hat{\beta}_t^*$ is the minimum variance hedge ratio, the variance of R_t is the smallest possible. The hedge effectiveness (HE) in equation (10) is used to evaluate the performance of each commodity with different lengths to maturity.

For comparison purposes, we also consider a naïve hedge scenario under which airlines cross hedge 100% of their jet fuel, i.e., constant hedge ratio = 1. Additionally, the variance of R_t based on the constant hedge ratios from the OLS models is computed to assess volatility reduction in equation (10) as an alternative to the adjusted R^2 measure of hedging performance. Table 4 displays the variances of portfolio returns for the one-day hedge horizon and the hedge effectiveness of each oil proxy with respect to the contract maturity.

It is evident from the results in Table 4 that heating oil outperforms its counterparts as a cross hedge proxy for jet fuel for a one-day hedge horizon for all maturities up to 12 months as indicated by the higher HE, and a heating oil contract maturing in one month is most effective compared with contracts with a longer maturity. Based on the estimated HE values in Table 4, for a one-day hedge horizon, a one-month heating oil futures is estimated to reduce returns volatility by about 64% to 67% over an unhedged portfolio. Also, WTI appears to be slightly more appealing than Brent, and gasoil is the least performing of the four for the daily hedge horizon. All models in Table 4 predict that hedge effectiveness decreases for contracts longer than three months in maturity for WTI, Brent, and gasoil.

For weekly and monthly horizons, the hedging performance of each energy futures is examined by repeating the above process. We report the results in Tables 5 and 6. The results in the two tables show that heating oil remains the most effective regardless of the hedge horizon or the maturity, and heating oil contract maturing in one month is more desirable than those with further maturities.

Contrary to its ineffectiveness for a one-day horizon, the hedging performance of gasoil improved considerably under a one-week holding period (see Table 5). Generally, the results in Table 5 show that WTI, Brent, and gasoil contracts maturing in three months are more desirable than other maturities.

On the other hand, the effects of maturity on hedge effectiveness are mixed for a one-month hedge horizon (Table 6). The performance of gasoil dissipates, but its effectiveness remains over 40% depending on the model and the distance to maturity. The performance of heating oil over a one-month holding period is nearly the same as its effectiveness over a one-week horizon.

The lower HE values for WTI as shown in Tables 5 and 6 mean that the performance of WTI as a hedge proxy for jet fuel is less desirable compared with the other commodities over a one-week (in Table 5) or a monthly horizon (see Table 6). Brent is as suitable as gasoil for weekly and monthly horizons, but while gasoil is a better proxy for contracts maturing in three months or less, and Brent contracts with three months or longer maturities are more appealing.

In Tables 4-6, the OLS constant hedge strategy appears to dominate all models in producing the highest hedge effectiveness. This is expected since the OLS constant hedge ratio minimizes the unconditional variance, while the time-varying GARCH hedge ratios minimize the conditional variance, and the Ederington's (1979) *HE* measure in equation (10) is based on the unconditional variance (Lien 2009).

Table 3: VECM-GARCH Results for 1-month Futures Contract with 1-Day Hedge Horizon†

WTI

BEKK	Coef.	Std. Error	CCC	Coef.	Std. Error
α_0	-0.009586	0.003556	α_0	-0.009737	0.003554
α_1	0.000751	0.000253	α_1	0.000891	0.000254
β_0	0.004255	0.003629	β_0	0.006671	0.003506
β_1	0.000888	0.000256	β_1	0.000945	0.000249
c_{11}	0.000008	0.000001	c_1	0.000008	0.000001
c_{12}	0.000007	0.000001	a_1	0.060170	0.005411
c_{22}	0.000009	0.000001	b_1	0.930280	0.005784
a_{11}	0.245741	0.009361	c_2	0.000008	0.000001
a_{22}	0.235735	0.010364	a_2	0.052571	0.005479
b_{11}	0.963444	0.002547	b_2	0.934688	0.006663
b_{22}	0.963296	0.003091	ρ	0.775963	0.006396
tdist	6.265632	0.315210	tdist	5.637287	0.283861
Log likelihood		26703.06	Log likelihood		26557.64

BRENT

BEKK	Coef.	Std. Error	CCC	Coef.	Std. Error
α_0	-0.022281	0.004450	α_0	-0.023349	0.004570
α_1	0.000307	0.000251	α_1	0.000372	0.000248
β_0	0.003724	0.003968	β_0	0.005733	0.003728
β_1	0.000843	0.000237	β_1	0.000809	0.000224
c_{11}	0.000006	0.000001	c_1	0.000004	0.000001
c_{12}	0.000004	0.000001	a_1	0.054826	0.004744
c_{22}	0.000004	0.000001	b_1	0.943505	0.004462
a_{11}	0.239604	0.008853	c_2	0.000002	0.000001
a_{22}	0.223838	0.009325	a_2	0.046918	0.004648
b_{11}	0.967745	0.002195	b_2	0.953248	0.004417
b_{22}	0.971761	0.002199	ρ	0.779055	0.006301
tdist	5.978026	0.322753	tdist	5.332882	0.275055
Log likelihood		27163.27	Log likelihood		26968.37

GASOIL

BEKK	Coef.	Std. Error	CCC	Coef.	Std. Error
α_0	-0.005558	0.002716	α_0	-0.039301	0.007502
α_1	0.000592	0.000256	α_1	0.000466	0.000257
β_0	0.009002	0.001561	β_0	0.068511	0.005783
β_1	0.000390	0.000163	β_1	0.000876	0.000214
c_{11}	0.000004	0.000001	c_1	0.000003	0.000001
c_{12}	0.000001	0.000000	a_1	0.051087	0.005064
c_{22}	0.000001	0.000000	b_1	0.944803	0.005189
a_{11}	0.227384	0.009706	c_2	0.000001	0.000000
a_{22}	0.162231	0.008488	a_2	0.035465	0.003887
b_{11}	0.970690	0.002443	b_2	0.962842	0.004027
b_{22}	0.985551	0.001446	ρ	0.595401	0.010297
tdist	8.054231	0.560715	tdist	6.724045	0.402837
Log likelihood		27562.2	Log likelihood		26190.29

HEATING OIL

BEKK	Coef.	Std. Error	CCC	Coef.	Std. Error
α_0	-0.003100	0.002686	α_0	0.005887	0.007268
α_1	0.000559	0.000233	α_1	0.000781	0.000233
β_0	0.003363	0.001894	β_0	0.026102	0.006405
β_1	0.000472	0.000178	β_1	0.000752	0.000221
c_{11}	0.000005	0.000001	c_1	0.000010	0.000002
c_{12}	0.000003	0.000001	a_1	0.068371	0.006254
c_{22}	0.000003	0.000000	b_1	0.939469	0.004302
a_{11}	0.241407	0.008390	c_2	0.000007	0.000001
a_{22}	0.221455	0.009171	a_2	0.053460	0.005589
b_{11}	0.968010	0.001925	b_2	0.951366	0.004336
b_{22}	0.972771	0.002041	ρ	0.924500	0.002419
tdist	5.323474	0.267389	tdist	3.341417	0.131325
Log likelihood		29342.08	Log likelihood		28827.62

†The CCC model is specified by equations (5) and (6), while the BEKK model is given in equations (7) and (8).

Out-of-Sample Hedging Performance

The analysis so far provides a glimpse of the historical hedge effectiveness of each commodity futures. The results yield only *ex ante* information that is useful for firms in identifying a reasonably effective hedging instrument and potential hedging strategy. However, the hedging performances must be evaluated to determine whether the models hold in the future, given that what works best within the sample does not necessarily work well outside the sample. If heating oil is used as a cross hedge proxy for jet fuel, it is important for airlines to continue to evaluate the hedging performance on an ongoing basis.

For this we apply the one-period-ahead out-of-sample forecasting approach on the models. Since heating oil dominates the other three commodities for cross hedging jet fuel, the out-of-sample analysis on heating oil is conducted. At first, we split the full sample into an estimation subsample and a forecasting sample. The estimation subsample contains the first 70% of the observations, and the forecasting sample contains the remaining 30%, which we use for out-of-sample evaluation. The former subsample is used to estimate the parameters in the GARCH models, and subsequently the estimated parameters are used to forecast H_t and the dynamic hedge ratio for the next period. Once the first forecasted values are obtained, the estimation subsample (70% of total observations) is rolled over to the next period to generate another one-period-ahead forecast. This process is repeated on a period-by-period basis from the first observation of the forecasting sample to the end of the sample. The process is implemented for each maturity using different hedge horizons. Specifically, for each GARCH specification, the forecasting sample for the daily hedge horizon consists of 1,495 forecasted portfolios (March 26, 2008 - February 27, 2014), the weekly horizon has 310 (starting from March 24, 2008), and the monthly (4-weekly) hedge horizon has 156 forecasts (starting from March 10, 2008).

The forecasted portfolio returns obtained from the models are then used to calculate hedge effectiveness. For comparison purposes, we also compute the variances and the hedge effectiveness of the naïve and the OLS constant hedge portfolios for the forecasting sample periods. The results are reported in Table 7.

In Table 7, regardless of the hedge horizon, the hedge effectiveness of heating oil is higher for one- and three-month contracts; the hedging performance drops slightly for contracts with longer maturities. Additionally, the hedges over the weekly and monthly horizons are more effective. In a nutshell, the out-of-sample results indicate that heating oil is a reliable cross hedge proxy for jet fuel, especially for contracts maturing in three months or less.

Table 4: Hedge Effectiveness for 1-Day Horizon†

		BEKK	*CCC*	*Naïve*	*OLS*
WTI					
1-month	$Var(R_t^*)$	0.3063	0.3231	0.3610	0.3186
	HE	0.4931	0.4681	0.4084	0.4755
3-month	$Var(R_t^*)$	0.2733	0.2775	0.2756	0.2733
	HE	0.5500	0.5431	0.5424	0.5462
6-month	$Var(R_t^*)$	0.2790	0.2851	0.2840	0.2837
	HE	0.5406	0.5306	0.5325	0.5329
9-month	$Var(R_t^*)$	0.2907	0.2974	0.2982	0.2963
	HE	0.5214	0.5104	0.5091	0.5121
12-month	$Var(R_t^*)$	0.3027	0.3103	0.3127	0.3105
	HE	0.5017	0.4892	0.4852	0.4888
Brent					
1-month	$Var(R_t^*)$	0.3087	0.3200	0.3246	0.3087
	HE	0.4919	0.4732	0.4657	0.4938
3-month	$Var(R_t^*)$	0.2867	0.2998	0.2863	0.2851
	HE	0.5279	0.5065	0.5287	0.5307
6-month	$Var(R_t^*)$	0.2948	0.3075	0.2939	0.2935
	HE	0.5146	0.4937	0.5161	0.5167
9-month	$Var(R_t^*)$	0.3127	0.3262	0.3125	0.3110
	HE	0.4852	0.4630	0.4855	0.4879
12-month	$Var(R_t^*)$	0.3267	0.3423	0.3289	0.3268
	HE	0.4622	0.4366	0.4585	0.4620

		BEKK	*CCC*	*Naïve*	*OLS*
Gasoil					
1-month	$Var(R_t^*)$	0.4359	0.4348	0.4735	0.4285
	HE	0.2823	0.2842	0.2204	0.2946
3-month	$Var(R_t^*)$	0.4112	0.4089	0.4208	0.4065
	HE	0.3231	0.3269	0.3072	0.3308
6-month	$Var(R_t^*)$	0.4243	0.4220	0.4263	0.4211
	HE	0.3014	0.3053	0.2983	0.3068
9-month	$Var(R_t^*)$	0.4343	0.4333	0.4337	0.4314
	HE	0.2851	0.2867	0.2861	0.2894
11-month	$Var(R_t^*)$	0.4412	0.4403	0.4403	0.4385
	HE	0.2737	0.2751	0.2751	0.2781
Heating Oil					
1-month	$Var(R_t^*)$	0.1989	0.2168	0.2078	0.2024
	HE	0.6726	0.6431	0.6579	0.6669
3-month	$Var(R_t^*)$	0.2090	0.2190	0.2037	0.2031
	HE	0.6560	0.6394	0.6646	0.6656
6-month	$Var(R_t^*)$	0.2383	0.2526	0.2382	0.2337
	HE	0.6077	0.5842	0.6079	0.6152
9-month	$Var(R_t^*)$	0.2518	0.2623	0.2590	0.2498
	HE	0.5855	0.5681	0.5735	0.5888
12-month	$Var(R_t^*)$	0.2634	0.2748	0.2730	0.2616
	HE	0.5664	0.5477	0.5506	0.5693

† The values of $Var(R_t^*)$ are multiplied by 10^3. Data frequency is daily; #obs = 4984. Hedge effectiveness, *HE*, is calculated based on equation (10).

Table 5: Hedge Effectiveness for 1-Week Horizon†

		BEKK	CCC	Naïve	OLS			BEKK	CCC	Naïve	OLS
WTI						**Gasoil**					
1-month	$Var(R_t^*)$	0.1396	0.1451	0.1500	0.1364	1-month	$Var(R_t^*)$	0.1255	0.1256	0.1201	0.1173
	HE	0.4727	0.4522	0.4335	0.4849		*HE*	0.5261	0.5256	0.5466	0.5571
3-month	$Var(R_t^*)$	0.1250	0.1304	0.1229	0.1218	3-month	$Var(R_t^*)$	0.1253	0.1270	0.1161	0.1161
	HE	0.5281	0.5077	0.5358	0.5399		*HE*	0.5268	0.5205	0.5617	0.5617
6-month	$Var(R_t^*)$	0.1276	0.1317	0.1245	0.1244	6-month	$Var(R_t^*)$	0.1332	0.1330	0.1266	0.1257
	HE	0.5183	0.5028	0.5298	0.5303		*HE*	0.4969	0.4976	0.5220	0.5253
9-month	$Var(R_t^*)$	0.1318	0.1344	0.1298	0.1286	9-month	$Var(R_t^*)$	0.1422	0.1431	0.1375	0.1353
	HE	0.5024	0.4924	0.5099	0.5144		*HE*	0.4631	0.4596	0.4807	0.4891
12-month	$Var(R_t^*)$	0.1372	0.1391	0.1362	0.1340	11-month	$Var(R_t^*)$	0.1448	0.1466	0.1426	0.1436
	HE	0.4819	0.4747	0.4856	0.4941		*HE*	0.4532	0.4463	0.4615	0.4577
Brent						**Heating Oil**					
1-month	$Var(R_t^*)$	0.1282	0.1330	0.1284	0.1235	1-month	$Var(R_t^*)$	0.0801	0.0812	0.0759	0.0753
	HE	0.5158	0.4977	0.5151	0.5335		*HE*	0.6974	0.6936	0.7134	0.7157
3-month	$Var(R_t^*)$	0.1244	0.1275	0.1177	0.1244	3-month	$Var(R_t^*)$	0.0908	0.0915	0.0835	0.0829
	HE	0.5302	0.5185	0.5556	0.5302		*HE*	0.6570	0.6545	0.6846	0.6869
6-month	$Var(R_t^*)$	0.1288	0.1313	0.1217	0.1212	6-month	$Var(R_t^*)$	0.1139	0.1143	0.1039	0.1139
	HE	0.5135	0.5041	0.5403	0.5424		*HE*	0.5700	0.5684	0.6074	0.6166
9-month	$Var(R_t^*)$	0.1334	0.1358	0.1275	0.1256	9-month	$Var(R_t^*)$	0.1159	0.1166	0.1164	0.1109
	HE	0.4961	0.4872	0.5185	0.5258		*HE*	0.5623	0.5597	0.5605	0.5812
12-month	$Var(R_t^*)$	0.1406	0.1411	0.1352	0.1325	12-month	$Var(R_t^*)$	0.1169	0.1169	0.1210	0.1124
	HE	0.4692	0.4673	0.4895	0.4998		*HE*	0.5585	0.5584	0.5431	0.5754

† The values of $Var(R_t^*)$ are multiplied by 10^2. Data frequency is weekly; #obs = 1031. Hedge effectiveness, *HE*, is calculated based on equation (10).

Table 6: Hedge Effectiveness for 1-Month Horizon†

		BEKK	*CCC*	*Naïve*	*OLS*
WTI					
1-month	$Var(R_t^*)$	0.0337	0.0328	0.0346	0.0301
	HE	0.3475	0.3649	0.3294	0.4175
3-month	$Var(R_t^*)$	0.0232	0.0342	0.0267	0.0259
	HE	0.5504	0.3380	0.4833	0.4983
6-month	$Var(R_t^*)$	0.0261	0.0301	0.0258	0.0258
	HE	0.4947	0.4164	0.5002	0.5009
9-month	$Var(R_t^*)$	0.0265	0.0283	0.0262	0.0262
	HE	0.4870	0.4517	0.4921	0.4925
12-month	$Var(R_t^*)$	0.0261	0.0279	0.0270	0.0268
	HE	0.4944	0.4591	0.4770	0.4799
Brent					
1-month	$Var(R_t^*)$	0.0284	0.0273	0.0278	0.0257
	HE	0.4519	0.4705	0.4642	0.5030
3-month	$Var(R_t^*)$	0.0251	0.0264	0.0245	0.0243
	HE	0.5146	0.4883	0.5263	0.5316
6-month	$Var(R_t^*)$	0.0258	0.0257	0.0246	0.1577
	HE	0.5029	0.5020	0.5243	0.5199
9-month	$Var(R_t^*)$	0.0251	0.0247	0.0251	0.0250
	HE	0.5150	0.5208	0.5157	0.5178
12-month	$Var(R_t^*)$	0.0247	0.0254	0.0260	0.0257
	HE	0.5238	0.5090	0.4983	0.5031

		BEKK	*CCC*	*Naïve*	*OLS*
Gasoil					
1-month	$Var(R_t^*)$	0.0246	0.0278	0.0284	0.0271
	HE	0.5246	0.4618	0.4518	0.4770
3-month	$Var(R_t^*)$	0.0239	0.0287	0.0271	0.0269
	HE	0.5380	0.4438	0.4773	0.4808
6-month	$Var(R_t^*)$	0.0235	0.0283	0.0267	0.0283
	HE	0.5459	0.4522	0.4530	0.4530
9-month	$Var(R_t^*)$	0.0249	0.0294	0.0295	0.0294
	HE	0.5193	0.4299	0.4305	0.4325
11-month	$Var(R_t^*)$	0.0259	0.0296	0.0300	0.0298
	HE	0.4992	0.4268	0.4207	0.4252
Heating Oil					
1-month	$Var(R_t^*)$	0.0152	0.0165	0.0151	0.0148
	HE	0.7072	0.6799	0.7093	0.7135
3-month	$Var(R_t^*)$	0.0162	0.0183	0.0168	0.0168
	HE	0.6867	0.6454	0.6749	0.6761
6-month	$Var(R_t^*)$	0.0211	0.0219	0.0205	0.0201
	HE	0.5936	0.5752	0.6042	0.6113
9-month	$Var(R_t^*)$	0.0218	0.0227	0.0224	0.0214
	HE	0.5794	0.5608	0.5686	0.5867
12-month	$Var(R_t^*)$	0.0203	0.0226	0.0226	0.0211
	HE	0.6090	0.5632	0.5639	0.5923

† Data frequency is 4-weekly; #obs = 1031. Hedge effectiveness, *HE*, is calculated based on equation (10).

Table 7: Out-of-Sample Hedge Effectiveness of Heating Oil†

		1-Day Hedge Horizon				1-Week Hedge Horizon				1-Month Hedge Horizon			
		BEKK	CCC	Naïve	OLS	BEKK	CCC	Naïve	OLS	BEKK	CCC	Naïve	OLS
1-month	$Var(R_t^*)$	0.1055	0.1150	0.1041	0.1032	0.4526	0.4830	0.3726	0.3721	0.0083	0.0089	0.0075	0.0075
	HE	0.7795	0.7597	0.7824	0.7844	0.8095	0.7967	0.8431	0.8434	0.8386	0.8269	0.8546	0.8546
3-month	$Var(R_t^*)$	0.1037	0.1130	0.0999	0.0998	0.5077	0.5557	0.4251	0.4249	0.0139	0.0112	0.0089	0.0088
	HE	0.7833	0.7638	0.7913	0.7914	0.7863	0.7661	0.8211	0.8211	0.7299	0.7831	0.8282	0.8294
6-month	$Var(R_t^*)$	0.1138	0.1217	0.1095	0.1083	0.5695	0.6553	0.5075	0.5042	0.0194	0.0132	0.0109	0.0106
	HE	0.7621	0.7457	0.7713	0.7737	0.7602	0.7241	0.7863	0.7877	0.6242	0.7449	0.7892	0.7938
9-month	$Var(R_t^*)$	0.1202	0.1266	0.1178	0.1146	0.5825	0.6602	0.5438	0.5302	0.0146	0.0101	0.0114	0.0107
	HE	0.7488	0.7355	0.7538	0.7605	0.7548	0.7221	0.7711	0.7768	0.7166	0.8044	0.7789	0.7922
12-month	$Var(R_t^*)$	0.1276	0.1333	0.1267	0.1219	0.5931	0.6492	0.5531	0.5241	0.0126	0.0100	0.0114	0.0104
	HE	0.7332	0.7215	0.7351	0.7453	0.7503	0.7267	0.7672	0.7794	0.7565	0.8069	0.7791	0.7994

† The values of daily and weekly $Var(R_t^*)$ are multiplied by 10^3. Hedge effectiveness, HE, is calculated based on equation (10).

CONCLUSIONS

Because of wild swings in oil commodity prices, airlines undertake considerable risk with jet fuel cross hedging. Ineffective hedges create substantial financial vulnerability and instability to airlines, which often incur considerable losses in their hedging programs. This paper examined the effectiveness of WTI, Brent, gasoil, and heating oil as cross hedge proxies for jet fuel. The findings shed light on the effects of hedge duration and distance to maturity on hedge effectiveness. Our results show that heating oil is the most suitable proxy of the four oil commodities regardless of the contract maturity and hedge horizon.

We find heating oil, rather than gasoil, to be a more suitable cross hedge proxy for jet fuel. This result contradicts the finding in Adams and Gerner (2012), which showed gasoil to be more superior. One plausible explanation for this is that Adams and Gerner (2012) used jet fuel spot prices from Amsterdam-Rotterdam-Antwerp (ARA), which are likely more correlated with the future prices of gasoil that is also traded in Europe (Adams and Gerner 2012). On the other hand, this study uses U.S. Gulf Coast jet fuel as the spot market and considers No. 2 heating oil traded on the NYMEX as a cross hedge commodity, thus heating oil is more suitable for U.S. jet fuel cross hedge. This may indicate that besides the hedge horizon and distance to maturity, hedge effectiveness is also location-sensitive. We find gasoil's performance to be the most inferior for a one-day holding period, but it improved considerably over a weekly horizon.

The out-of-sample results suggest that one- and three-month heating oil contracts are the most desirable over contracts with longer maturities. This result is consistent with an earlier finding by Turner and Lim (2015). However, since Turner and Lim (2015) only assumed a one-day hedge horizon, they did not examine the hedging performance over the weekly or monthly holding periods. In this study, we find that a one-week horizon is more favorable than daily and monthly holding periods. Overall, the one-day hedge horizon is not recommended for all commodities and maturities, and even though heating oil may be considered reasonably effective, the transaction costs associated with a daily horizon might be too high for the hedge to be considered economically sound.

In summary, the effects of hedging horizon and maturity on the performance of jet fuel proxies are commodity-specific. Heating oil outperforms all three other proxies, especially with a weekly hedge horizon and for contracts maturing in three months or less. Gasoil, WTI, and Brent all perform well with a weekly hedge horizon, but their performances declined with a monthly hedge horizon.

Acknowledgements

This study was funded in part by the Upper Great Plains Transportation Institute, North Dakota State University, Fargo, North Dakota. We are grateful to two anonymous referees and Prof. Michael Babcock, co-editor, for their constructive comments and suggestions.

Endnotes

1. Basis risk is the risk to a hedger as a result of the difference in the futures price and the spot price of a commodity.

2. A forward contract is a non-standardized contract between two parties that allow them to buy or sell an asset at a specific price at a specific time in the future. Unlike futures contracts that are exchange-traded, forward contracts are private agreements.

3. See Morrell and Swan (2006) for detailed discussions on futures, forwards, options, collars, and swaps.

4. In 2009, Ryanair's fuel cost per available seat mile rose by 39% and total fuel cost rose by a stunning 59% relative to the fuel costs in 2008 (Ryanair 2009).

5. Gasoil is the same as No. 2 fuel oil in the U.S., but it is the European designation for the product and traded in Europe (Turner and Lim 2015).

6. A hedge ratio is the ratio of the size of a position in a financial contract, such as a futures contract, to the size of the underlying asset.

7. A long position refers to a firm's position to buy an asset in the future, and a short position refers to a firm's position to sell an asset in the future. If a firm takes a long cash position and a short futures position, that means the firm sells futures contracts while buying jet fuel in the spot market.

8. Baba, Engle, Kraft, and Kroner (BEKK 1990). The diagonal BEKK that restricts off-diagonal elements of the coefficient matrices to be zero, and is therefore more parsimonious than the general form BEKK.

9. Because gasoil futures price data for 12-month rolling contracts were not retrievable from Bloomberg at the time of this research, we used the data for 11-month rolling contracts as a proxy.

10. Results from the ADF and PP tests are consistent with those produced by the KPSS test. Hence, the PP and ADF test results are not reported here.

11. Kurtosis measures the thickness of the tails of a distribution. A distribution with thick tails are leptokurtic. In investment, a leptokurtic distribution means more risk as outlier events are more likely to occur. Since the distribution of the GARCH residuals is leptokurtic, we assume the distribution is Student's *t* as opposed to normal.

References

Adams, Z., and M. Gerner. "Cross Hedging Jet-fuel Price Exposure." *Energy Economics* 34 (5), (2012): 1301 - 1309.

Argus. "Argus White Paper: Argus Jet Fuel Price Assessments." available at: https://media.argusmedia.com/~/media/Files/PDFs/White%20Paper/Jet-Fuel-Assessments.pdf (accessed 31 May 2013), 2012.

Baba, Y., R.F. Engle, D.F. Kraft, and K.F. Kroner. "Multivariate Simultaneous Generalized ARCH." Mimeo, Department of Economics, University of California – San Diego, 1990.

Baillie, R.T., and R.J. Myers. “Bivariate GARCH Estimation of the Optimal Commodity Futures Hedge.” *Journal of Applied Econometrics* 6 (2), (1991): 109-124.

Bauwens, L., S. Laurent, and J.V.K. Rombouts. “Multivariate GARCH Models: A Survey.” *Journal of Applied Econometrics* 21 (1), (2006): 79-109.

Bollerslev, T. “Modeling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model.” *Review of Economics and Statistics* 72 (3), (1990): 498-505.

Brooks, R. “Samuelson Hypothesis and Carry Arbitrage.” *Journal of Derivatives* 20 (2), (2012): 37-65.

Cecchetti, S.G., R.E. Cumby, and S. Figlewski. “Estimation of Optimal Futures Hedge.” *Review of Economics and Statistics* 70 (4), (1988): 623-630.

Chen, S.S., C.F. Lee, and K. Shrestha. “Futures Hedge Ratio: A Review.” *The Quarterly Review of Economics and Finance* 43 (3), (2003): 433-465.

CME Group. “Derivatives and Hedge Accounting.” available at: http://www.cmegroup.com/education/files/derivatives-and-hedge-accounting.pdf (accessed 1 March 2013), 2012.

Corley, M. “Mitigate Not Speculate.” *Airline Economics* 17, (2013): 74-75.

Ederington, L.H. “The Hedging Performance of the New Futures Markets.” *Journal of Finance* 34 (1), (1979): 157-170.

Engle, R.F., and K.F. Kroner. “Multivariate Simultaneous GARCH.” *Econometric Theory* 11 (3), (1995): 122-150.

Finnerty, J.D., and D. Grant. “Alternative Approaches to Testing Effectiveness under SFAS No. 133.” *Accounting Horizons* 16 (2), (2002): 95-108.

Gronwald, M. “A Characterization of Oil Price Behavior- Evidence from Jump Models,” *Energy Economics* 34 (5), (2012): 1310-1317.

Halls, M. “To Hedge or Not to Hedge.” *Airfinance Journal,* (2005): 27-29.

Holmes, P. “Stock Index Futures Hedging: Hedge Ratio Estimation, Duration, Effects, Expiration Effects and Hedge Ratio Stability.” *Journal of Business Finance and Accounting* 23 (1), 1996: 63-77.

Ledoit, O., P. Santa-Clara, and M. Wolf. “Flexible Multivariate GARCH Modeling with an Application to International Stock Markets.” *Review of Economics and Statistics* 85 (3), (2003): 735-747.

Johnson, L.L. “The Theory of Hedging and Speculation in Commodity Futures.” *Review of Economic Studies* 27 (3), (1960): 139-151.

Kroner, K.F., and J. Sultan. “Time-varying Distributions and Dynamic Hedging with Foreign Currency Futures.” *Journal of Financial and Quantitative Analysis* 28 (4), (1993): 535-551.

Lien, D. “A Note on the Hedge Effectiveness of GARCH Models.” *International Review of Economics and Finance* 18 (1), (2009): 110-112.

Lim, S.H., and Y. Hong. "Fuel Hedging and Airline Operating Costs." *Journal of Air Transport Management* 36, (2014): 33-40.

Lindahl, M. "Minimum Variance Hedge Ratios for Stock Index Futures: Duration and Expectation Effects." *Journal of Futures Markets* 12 (1), (1992): 33-53.

Malliaris, A.G., and J.L. Urrutia. "The Impact of the Lengths of Estimation Periods and Hedging Horizons on the Effectiveness of a Hedge: Evidence from Foreign Currency Futures." *Journal of Futures Market* 11(3), (1991): 271-289.

Morrell, P., and W. Swan. "Airline Jet Fuel Hedging: Theory and Practice." *Transport Review* 26 (6), (2006): 713-730.

Myers, R. "Estimating Time-varying Optimal Hedge Ratios on Futures Markets." *Journal of Futures Markets* 11 (1), (1991): 39-53.

Park, T.H., and L.N. Switzer. "Bivariate GARCH Estimation of the Optimal Hedge Ratios for Stock Index Futures: A Note." *Journal of Futures Markets* 15 (1), (1995): 61-67.

Rampini, A.A., A. Sufi, and S. Viswanathan. "Dynamic Risk Management." *Journal of Financial Economics* 111 (2), (2014): 271-296.

Ripple, R.D., and I. A. Moosa. "Hedge Effectiveness and Futures Contract Maturity: The Case of NYMEX Crude Oil Futures." *Applied Financial Economics* 17 (9), (2007): 683-689.

Ryanair. "Annual Reports." Available at: http://corporate.ryanair.com/investors/ (accessed 12 January 2013), (various years).

Samuelson, P.A "Proof That Properly Anticipated Prices Fluctuate Randomly." *Industrial Management Review* 6 (2), (1965): 41-49.

Southwest Airlines "Form 10K for the Fiscal Year Ending Dec 31, 2011 (Filing date: February 9, 2012)." Available at: http://www.investorroom.com (accessed January 23 2013), 2012.

Southwest Airlines. "Form 10K for the Fiscal Year Ending Dec 31, 2012 (Filing date: February 7, 2013)." Available at: http://www.investorroom.com (accessed May 4 2013), 2013.

Southwest Airlines. "Form 10K for the fiscal year ending Dec 31, 2014 (Filing date: February 6, 2015)." Available at: http://www.investorroom.com (accessed November 30 2015), 2015.

Turner, P.A., and S.H. Lim. "Hedging Jet Fuel Price Risk: The Case of U.S. Passenger Airlines." *Journal of Air Transport Management* 44, (2015): 54-64.

Zhang, H. "Effect of Derivative Accounting Rule on Corporate Risk Management Behavior." *Journal of Accounting and Economics* 47 (3), (2009): 244-264.

***Siew Hoon Lim** is an associate professor in the Department of Agribusiness and Applied Economics at North Dakota State University. Her research interests are in transportation economics, production economics, industrial organization and regional development. She received her Ph.D. in economics from the University of Georgia.*

***Peter A. Turner** received his M.S. in agribusiness and applied economics from North Dakota State University. His research interest is in transportation finance.*

Dedicated Energy Crop Supply Chain and Associated Feedstock Transportation Emissions: A Case Study of Tennessee

by T. Edward Yu, James A. Larson, Burton C. English, Joshua S. Fu, Jimmy Calcagno, III, and Bradly Wilson

This study minimizes total cost for single-feedstock supply chains of two dedicated energy crops, perennial switchgrass and biomass sorghum, in Tennessee using a spatial optimization model. Greenhouse gas emissions from the transport of feedstock to the conversion facility were estimated for respective feedstock supply chains. Results show that different demand for land types from two feedstocks and the geographically diverse landscape across the state affect the economics of bioenergy crops supply chains and feedstock transportation emissions. Switchgrass is more suitable than biomass sorghum for biofuel production in Tennessee based on the supply chains cost and feedstock hauling emissions.

INTRODUCTION

Biomass feedstock produced from dedicated energy crops and the residues of crop and forest have great potential for the production of bio-based fuels, power, and products in the United States (Turhollow et al. 2014). Various federal policy programs, such as blender tax credits, federal legislation of biofuel mandates, and the grant/loan program for establishing biomass feedstocks and constructing conversion facilities under the Food, Conservation, and Energy Act of 2008 (i.e., 2008 Farm Bill), have been implemented to accelerate the commercialization of advanced biofuels. The development of biomass-based value chains is also a major focus of bioenergy sector development in many states. Among others, the Tennessee Biofuels Initiative (TBI) is a state sponsored program to foster the development of the biofuels sector using switchgrass in Tennessee (Tiller 2011). The current progress of conversion technologies for cellulosic biofuel production at a pilot facility created under the TBI has motivated discussion about developing a commercial-scale cellulosic biofuel plant in Tennessee.

The amounts of biomass required to supply a commercial-scale conversion facility are significant given that biomass has low energy density. In addition, most of the potential lands for biomass production in Tennessee are currently idled or are used for less transportation-intensive traditional crop activities, such as pasture. Converting agricultural lands to biomass production implies additional traffic on roadways that connect fields and the conversion facility. Because more truck traffic to haul biomass is expected for an industrialized biofuel sector, one related potential environmental issue is increased emissions from hauling feedstock to the conversion facility. This environmental issue is presumably important because road transportation is a major source of greenhouse gas (GHG) emissions (Fürst and Oberhofer 2012).

Switchgrass and biomass sorghum have been considered as potential feedstocks for biofuel production in the southeast region (Turhollow et al. 2014). Switchgrass has consistent yields over diverse weather conditions and requires relatively low inputs compared with field crops (Wright and Turhollow 2010). Biomass sorghum also performs well in a wide range of soil types and drought conditions (Rooney et al. 2007). Both energy crops are capable of producing high biomass yields on marginal soils common to the region, including Tennessee. Switchgrass is a perennial grass which can be planted on pasture and croplands, while biomass sorghum as an annual crop is generally cultivated on cropland. In Tennessee, croplands are primarily located in the west side of the state given the flat terrain near the Mississippi River, while hay and pasturelands are common in the eastern region because of the varied topography related to the Appalachian Mountains. Different demand for land types from two energy crops and the geographically diverse landscape across the state presumably have different effects on land use for feedstock production and the dispersion of the feedstock draw area in Tennessee, which consequently influences the emissions from trucking feedstock to the conversion facility.

Given the potential for developing a biomass-based bioenergy industry in Tennessee, this study aims to achieve two objectives: 1) to evaluate the economics of the two dedicated energy crops' supply chains in various regions of the state, and 2) to assess the transportation emissions produced from hauling biomass feedstocks to the conversion facility with the least-cost supply chains by region identified in Objective 1. Our analysis generates insights regarding the impacts of crop systems and spatial characteristics on feedstock cost and GHG emissions of feedstock transportation in different regions. This information can benefit bioenergy sector stakeholders, including farmers, private investors, local communities, and regional development agencies.

LITERATURE REVIEW

Economics of biomass supply chains has been a major focus in the literature of bioenergy because the cost of feedstock supply chains is very influential to the commercialization of cellulosic biofuels (Hess et al. 2007). The biomass feedstock supply chain includes activities of feedstock production, harvest, storage, and transportation from field to conversion facility. The delivered cost of biomass feedstock can be influenced by the characteristics at each step of the supply chain, such as the type of harvesting method (e.g., bale or chop), choice of preprocessing operation (e.g., compression, pelletization), storage method used (e.g., outdoor or indoor), and mode of transportation (e.g., truck, rail, ocean). An extensive survey of recent literature in economic analysis of biomass and biofuel supply chains can be found in Sharma et al. (2013) and Mafakheri and Nasiri (2014). A brief review of the studies focusing on the transportation element in feedstock and biofuel supply chains is offered in this section.

Cundiff et al. (1997) developed a two-stage linear programming model to minimize the delivery cost of switchgrass through scheduling management for an ethanol plant in Virginia. Considering feedstock yield variations during different growing and harvest conditions, their findings suggest that average transportation cost was approximate \$8−\$10/dry metric ton (Mg) for an average travel distance of 22 km. Morrow et al. (2006) developed a transportation distance optimization model to minimize costs of distributing a range of ethanol blends (E5, E10, and E16) to U.S. metropolitan areas. They concluded that pipeline is the most cost effective means for ethanol transportation and emphasized the importance of an efficient transportation system for the competitiveness of the U.S. biofuel industry. Ekşioğlu et al. (2010) applied a mixed-integer programming model to minimize the delivery cost of biofuels by determining the mode use, shipment schedule, shipment size, production, and inventory schedule in a Mississippi case study. Barge and rail were considered for feedstock transportation and their results showed that barge is a more economic mode when demand for feedstock increases. Roni et al. (2014) analyzed the rail cost of biofuel and biomass using Surface Transportation Board's Waybill data, and derived the relationship between rail cost and car type, shipment size, commodity type, and rail movement type for both biofuel and biomass.

A number of studies have applied a geographic information system (GIS) to locate the potential sources of feedstock, determine location of biorefineries, and assess the transportation cost of feedstock or biofuel. Khachatryan et al. (2009) applied GIS to examine the availability of agricultural crop residue for cellulosic ethanol in the state of Washington and estimated the feedstock farm gate cost and transportation cost. They derived a supply curve of feedstock and suggested that plant capacity, transportation distances, and fuel price are influential to feedstock cost. Freppaz et al. (2004) integrated the GIS tool and mathematical programming in a Decision Support System to evaluate the availability of forest biomass and determine the location and size of plants in Val Bormida, Italy. Their results showed that local biomass availability can support 16% of energy need in the region at a reasonable cost. Marvin et al. (2012) estimated the net present value of a biomass-to-ethanol supply chain using a mixed-integer programming model and spatial data. Considering five agricultural residues in nine states in the U.S. midwest, the model determined the optimal locations and capacities of biofuel plants and biomass harvest and distribution. Using high resolution spatial data in Tennessee generated from GIS, Larson et al. (2015) assessed the plant gate cost of switchgrass using a mixed-integer programming model and evaluated the impact of dry matter loss during storage on the distribution of feedstock. They concluded that the storage loss is influential to the schedule of feedstock delivery and pattern.

More recent attention has been drawn to the environmental or social impacts of increased traffic induced by biomass feedstock supply chains. For instance, Kumar et al. (2006) suggested that the projected increase in truck traffic is likely to increase public resistance if the plant is located close to a community, and that rail transport reduces the number of loads and produces less emissions and congestion. Mahmudi and Flynn (2006) found that while rail shipments of biomass feedstock reduces emissions and congestion, it is not economical unless the shipping distance exceeds 120 miles. Tyner and Rismiller (2010) evaluated the impact of establishing a cellulosic biofuel industry on local road infrastructure in Indiana and suggested that considerable truckloads and high vehicle trip miles (VTM) surrounding each biofuel plant are anticipated. Moreover, the cellulosic biofuel industry would generate two to five times more VTM per gallon of biofuel, or up to 255% more ton-miles per gallon of biofuel compared with the existing grain-based biofuel industry. Jäppinen et al. (2011) indicated that it is crucial to consider local conditions, including the properties of the transportation network for hauling feedstock, when evaluating the sustainability of biomass-based energy production. Jäppinen et al. (2013) evaluated two case studies of wood chips supply chains and found that rail transportation to supplement direct truck transportation for wood chips may reduce supply chain GHG emissions. Also, biomass availability and modes of transportation to a given site should be taken into account when assessing GHG emissions in a biomass supply chain.

The aforementioned studies have highlighted the importance of the transportation sector in an efficient biomass and biofuel supply chain, and the concern of environmental and social impact of high traffic volume related to feedstock transportation. The current study complements the literature by analyzing the impacts of diverse crop systems and spatial characteristics on feedstock transportation cost and GHG emissions through an empirical study of comparing two potential energy crops (switchgrass and biomass sorghum) in Tennessee.

METHODS AND DATA

The analysis of supply chain costs of switchgrass and biomass sorghum and GHG emissions from transporting the feedstock to a conversion facility was divided into two major steps. First, the least-cost feedstock draw area and location of the conversion facility was identified for each of three regions in Tennessee (eastern, central, and western) by the Bioenergy Site and Technology Assessment (BeSTA) model developed in Larson et al. (2015). The cost-minimization solution located the most efficient road links within the feedstock draw area to the biorefinery based on the real road network for each region. Second, the additional emissions produced from feedstock transportation were estimated by applying an emission modeling system developed by the U.S. Environmental Protection Agency (US EPA 2012) to the vehicle traffic flow data generated in the first step.

The capacity of the commercial-scale conversion facility was assumed to be 50 million gallons per year (MGY) of biofuel (Tembo et al. 2003). The conversion facility considered in this study was a single-feedstock conversion facility that would not process mixed feedstock. Supply chain costs were evaluated for large rectangular bale harvest, storage, and transportation, a commonly used system for the harvest and storage of hay that can also be used for switchgrass (Mooney et al. 2012). The potential feedstock supply area includes Tennessee and a buffer area of 50 miles along the state's border to allow facilities to source feedstock from adjacent states if biofuel plants are sited near the border. Three geographic regions (eastern, central, and western) capture the spatial variations as defined by University of Tennessee Extension (University of Tennessee 2014). The potential locations for conversion facilities was assumed to be limited to feasible industrial parks with access to water, power, and roads, as well as sufficient storage space in each region.

Step 1: Determining Dedicated Energy Crops Supply Chains

The BeSTA model is a spatially oriented mixed-integer programming model that considers the sequence of production, harvest, storage, and transportation activities on a monthly basis within a year (Larson et al. 2015). The BeSTA model incorporates spatial variations and the within-year dynamics of switchgrass operations in the optimization of biomass feedstock supply chains, including location of the conversion facility, feedstock draw area, and feedstock delivery routes. The model objective function is to minimize opportunity cost of land, production cost, harvest cost, storage cost, and transportation cost of biomass feedstock to the conversion facility.

Certain constraints related to feedstock production, harvest, storage, and transportation activities were imposed in the BeSTA model. The annual supply of feedstock was constrained by feedstock yields and harvested area. In addition, monthly feedstock harvested in each land were subject to feedstock yields and available harvested area in the land unit. Moreover, total monthly harvested feedstock was limited by available harvest hours and machine availability. Constraints were also imposed on storage and transportation in each month. Monthly harvested feedstock was larger than feedstock shipped to the conversion facility after adjusting dry matter losses during transportation. Monthly harvested feedstock also must be greater than feedstock placed into storage in each month of harvest season. Delivered feedstock could not exceed accumulated storage of feedstock. In addition, feedstock deliveries were assumed to meet ethanol production each month. Additional constraints on the mass balance between harvest and inventory were imposed in the model. Details on the mathematical equations of the BeSTA model can be found in the Appendix.

Detailed spatial data were used for the supply chain analysis. The potential feedstock draw area was disaggregated into a vector database of contiguous five-square-mile land resource units based on remote sensing data within the feedstock supply regions. Public lands in the region were excluded from the analysis. The land resource units are the geographic units used to model areas in existing agricultural production activities (e.g., barley, corn, cotton, hay, oats, pasture, soybean, sorghum, and wheat) and energy crop production. Currently there is not a market for the two energy crops (switchgrass and biomass sorghum). Therefore, a breakeven price of each energy crop was determined by its production cost plus the net revenue from the next best agricultural production alternative, or land rent, whichever is higher (the *opportunity cost* of using the land for energy crop production) (Larson et al. 2015).

The street level network was applied to estimate transportation costs of biomass from the field to the facility. The hauling distance from the field to the conversion facility was calculated as the distance between the center point of the land resource unit in which feedstock is produced and the center point of the land resource unit where the conversion facility is located. The most accessible routes between land resource units and the facility were identified based on the speed limits of each type of roads following the hierarchy: 1) primary/major roads, 2) secondary roads, 3) local and rural roads, and 4) other roads. The five-axle 48-ft semi-tractor trailers were used to transport baled feedstock. The loading capacity of the flatbed trailer was assumed to carry 24 large square bales and totaled 14 dry tons per load. Transportation costs included labor, operating, and ownership costs of tractors with front-end loaders used for loading and unloading of bales, and semi-trucks with trailers used for transporting bales from the field to the conversion facility.

It was assumed that feedstock is harvested once per year using large rectangular balers. The bales are then placed into storage at the edge of the field until transported to a conversion facility. The harvest costs consisted of machinery operating and ownership costs plus labor costs for mowing, raking, baling, and loading operations. Storage costs included the materials (tarps and wooden pallets) used to protect bales stored on the edge of field, and the labor and tractor costs for material handling and baling. Dry matter losses for storage periods of up to 365 days for the large rectangular bales were modeled using estimated losses by time in storage for switchgrass from Mooney et al. (2012). Labor costs, operating and ownership costs for equipment and vehicles, and other inputs used for energy crop supply chains were obtained from Larson et al. (2010) and the University of Tennessee Institute of Agriculture (UTIA 2011).

Traditional crop yields at the sub-county level were taken from the SSURGO database maintained by the U.S. Department of Agriculture (U.S. Department of Agriculture 2014). Areas in each traditional crop for each land resource unit were taken from the Cropland Data Layer Database (U.S. Department of Agriculture 2011). Data for traditional crop prices were for the 2010-11 crop year (U.S. Department of Agriculture 2012). Switchgrass and biomass sorghum yields were obtained from Jager et al. (2010) and U.S. Department of Energy (2011). The yields of mature switchgrass was estimated around 8.0‒9.4 dry ton (dt) per acre. The yields of mature biomass sorghum after adjusting the lodging problem that causes stalks falling over during harvest ranged between 5.5 dt/acre and 12.0 dt/acre.

Step 2: Determining Truck Traffic Emissions from Feedstock Hauls

The Motor Vehicle Emissions Simulator (MOVES), an emission modeling program designed under the guidance of the U.S. EPA (U.S. EPA 2012), was used to estimate equivalent carbon dioxide (CO_2e) emissions from mobile sources. The version of the program used in this study is MOVES (2010b). MOVES is a regulatory mobile emission model that can be used to perform a quantitative estimate of project-level emission inventories (Vallamsundar and Lin 2011). MOVES can be used to simulate transportation emissions at various scales, such as individual roads and intersections at the county, region, and nationwide level. A number of recent studies have applied MOVES to estimate local or regional transportation emissions impacts of road projects or traffic management (e.g., Tao et al. 2011, Bigazzi and Figliozzi 2012, Papson et al. 2012, Xie et al. 2012, Mukherjee et al. 2013, Ghafghazi and Hatzopoulou 2014, Guo and Zhang 2014).

The following assumptions were made to facilitate the modeling of trucking emissions from feedstock transportation using MOVES. First, the *Project scale* option in MOVES was selected to permit emission modeling for individual road links. Second, the calendar year used in the model was 2010. Third, a representative month of the year that characterized each season of the year, i.e., April, July, October, and January, was used in the model to reduce computational time. Deliveries typically occurred from Monday through Friday during these aforementioned months. Fourth, meteorological data in a single county were used to represent all the surrounding counties in the area. Thus, Blount, Cumberland, Davidson, and Madison counties in Tennessee were selected given the presence of a regional airport located in each county. The surface hourly temperature and humidity data for these counties were collected from the National Climatic Data Center. Finally, the combination short-haul truck option was selected since it has the tractor-trailer type vehicle configuration. Emission factors generated from the models were then used to simulate the emissions from the additional truck traffic of feedstock hauls between farms and conversion facilities in the optimal energy crop supply chains determined in Step 1.

RESULTS

Economical Efficient Feedstock Supply Chains

Table 1 presents the total cost of switchgrass and biomass sorghum for a 50-MGY conversion facility. The total cost for delivering about 658,000 tons per year of switchgrass to the least-cost site in each of the three regions ranged between $45.9 million and $47.7 million. The average cost per dry ton of switchgrass in the eastern and central regions was relatively lower, about $70, while the cost increased to more than $72 per dry ton if switchgrass was produced in the west. The harvest cost accounted for more than half of the total supply chains cost, while transportation costs were estimated at more than 20% of total cost in each region. Production cost, including the opportunity cost of land, made up around 20% of total cost in all regions.

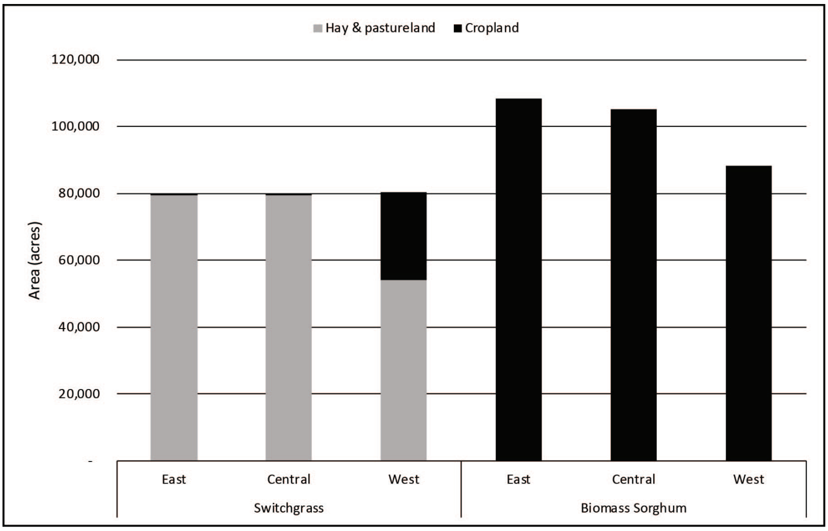
Table 1: Total Costs, Harvested Area, and Vehicle Miles Traveled (VMT) of Supplying Switchgrass and Biomass Sorghum to Conversion Facility by Region in Tennessee

	Switchgrass			Biomass Sorghum		
Region	**East**	**Central**	**West**	**East**	**Central**	**West**
Conversion Facility Location	McMinn County	Bedford County	Weakley County	Marion County	Giles County	Obion County
Total cost (million $)	**46.3**	**45.9**	**47.7**	**116.2**	**101.2**	**73.5**
Production (million $)	9.2	9.2	9.3	69.3	59.1	31.4
Harvest (million $)	23.9	23.9	24.0	28.3	27.8	25.2
Storage (million $)	3.3	3.3	3.3	3.3	3.3	3.3
Transportation (million $)	10.0	9.4	11.1	15.3	11.0	13.5
Cost per ton ($)	**70.4**	**69.7**	**72.4**	**176.7**	**153.8**	**111.7**
Total harvested area (1,000 acres)	**79.7**	**79.9**	**80.5**	**108.5**	**105.3**	**88.4**
VMT (1,000 miles)	**1,733**	**1,540**	**2,088**	**4,385**	**4,006**	**3,565**

Compared with the supply chain cost of switchgrass, biomass sorghum was a more expensive feedstock to produce in Tennessee. The total supply chain costs of biomass sorghum ranged between $73.5 million and $116.2 million across the three regions. In the eastern region, the total plant gate cost for biomass sorghum was nearly 150% higher than the cost of switchgrass using the same harvest and storage system. The feedstock costs in east Tennessee were the highest due to lower yields of biomass sorghum. In addition, the cost of hauling biomass sorghum to the conversion facility in east Tennessee was higher than for the sites in the central and western regions due to the larger draw area of biomass sorghum in east Tennessee. Land suitable for biomass sorghum production was smaller and less concentrated than in the other regions. Production costs of biomass sorghum were the highest among all costs. Unlike perennial switchgrass, biomass sorghum is an annual crop that is reestablished each year and had higher fertilizer and chemical costs that contributed to the higher production costs relative to switchgrass. Transportation cost accounted for about 11% to 18% of the total supply chain cost.

Harvested area for switchgrass in each of the three regions was similar, about 80,000 acres (see Table 1 and Figure 1). The total feedstock draw area was influenced by the yield of switchgrass in each land resource unit and the availability of lower opportunity cost of hay and pasture lands. As the opportunity cost of converting hay and pastureland to switchgrass production was the least among all crops in Tennessee, the available hay and pastureland in each land resource unit determines the density of switchgrass produced in that spatial unit. Figure 1 shows that nearly all area used for switchgrass production in east and central Tennessee were from hay and pasture lands. About one-third of harvested area was from croplands in west Tennessee given the relatively fewer acreages of hay and pasture within the region.

Figure 1: Land Use Change for Dedicated Energy Crop Production



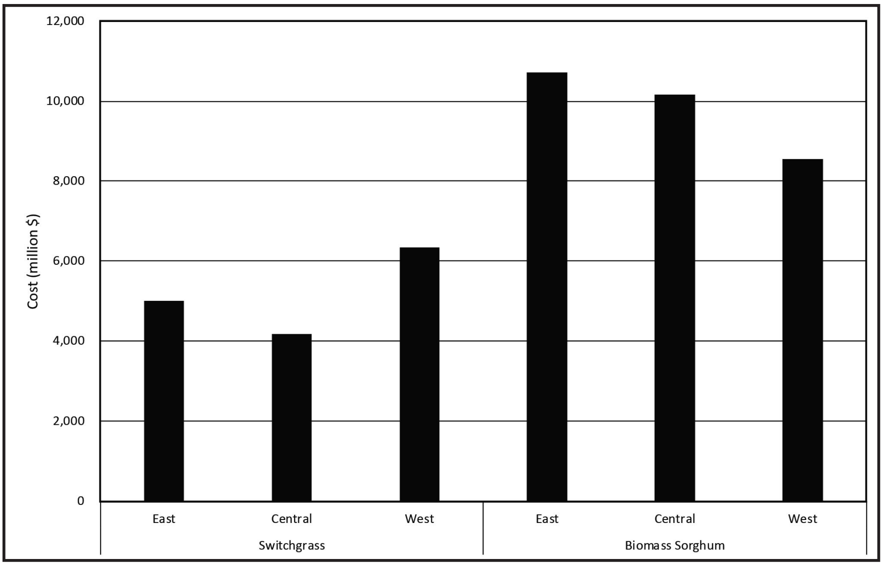
Harvested areas of biomass sorghum in east Tennessee were larger than in the central and western regions (Table 1 and Figure 1). The density of feedstock production in each land resource unit in the east region was smaller. In contrast, available crop land and yields of biomass sorghum in central and west Tennessee were higher, thus generating higher feedstock production density in land resource units and smaller feedstock draw area. Total harvested area in the eastern region reached more than 108,000 acres, while 20% less area [1 – (88.4 thousand acres / 108.5 thousand acres)] was needed for the conversion facility in west Tennessee. In addition, biomass sorghum can only be planted on crop lands, and a lack of available crop land in east Tennessee resulted in a larger area to produce biomass sorghum. The optimal locations of the conversion facilities in all three regions were close to the state's border, primarily driven by the yield of biomass sorghum and availability of croplands in land resource units.

GHG Emissions from Feedstock Transportation

Hauling switchgrass to the optimal site in west Tennessee generated the highest Vehicle Miles Traveled (VMT), over 2.0 million miles (Table 1). About 1.5 million miles were traveled for feedstock deliveries to the conversion facility in central Tennessee. Fewer truck emissions were produced than the selected sites in the other two regions given the smaller feedstock draw area and VMT (Figure 2). In contrast, VMTs were much higher for switchgrass in the western region due to a smaller availability of less expensive hay and pasture lands in the region. This region produced the most emissions from feedstock transportation, about 6,350 tons of CO_2e annually. For biomass sorghum, the VMT to the conversion facility in east Tennessee was the highest (Table 1), followed by the facility in the central region. Given the higher density of crop lands located in west Tennessee, the VMT of biomass sorghum to the conversion facility was the lowest among three regions, over

3.5 million miles. Feedstock transportation emissions of CO_2e of more than 8,500 tons per year were estimated for the region.

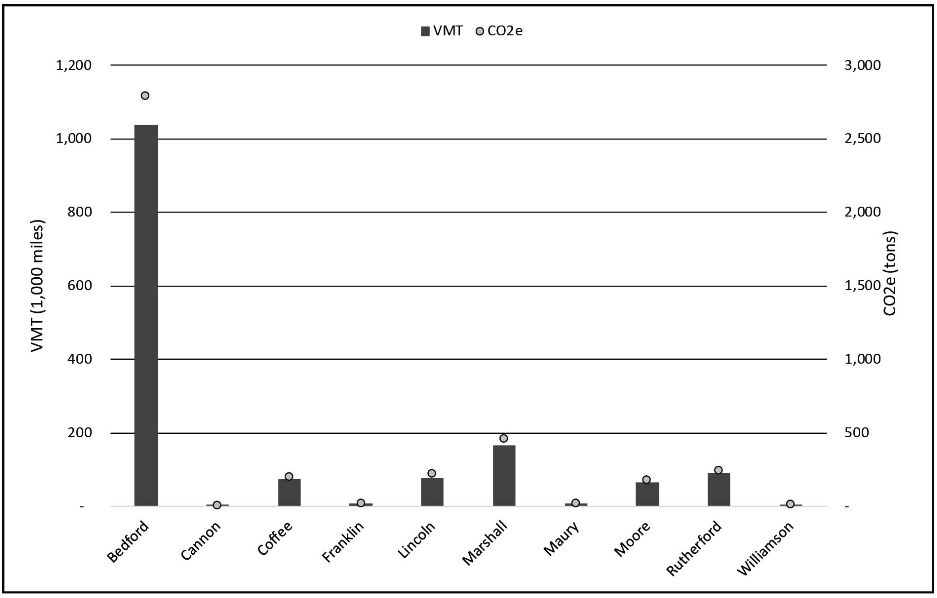
Figure 2: Transportation Emissions (CO2e) of Energy Crops to the Conversion Facility by Region in Tennessee



The summary of supply chain costs and CO_2e emissions of feedstock transportation by region in Table 1 and Figure 2 shows that switchgrass-based biofuels have much lower feedstock cost compared with biomass sorghum. Similarly, the emissions generated from hauling biomass sorghum to the conversion facility were much higher than that associated with transporting switchgrass due to the more dispersed feedstock draw area and the supply location of feedstock. Although the differences in the supply chains' cost of switchgrass among all three regions were small, the emissions produced from delivering feedstock to the conversion facility in the central region were clearly lower than the other two regions. Thus, the conversion facility using switchgrass as feedstock located in central Tennessee was found to be the most sustainable with the least economic costs and hauling emissions of feedstock.

The least cost location for a switchgrass biofuel plant was Bedford County in central Tennessee (see Table 1 and Figure 2). VMT and transportation emissions related to transport of switchgrass to the facility in the related counties are presented in Figure 3. With the facility located in Bedford County, more than 1.0 million trucking miles were expected due to feedstock delivery and resulted in nearly 2,800 tons of CO_2e per year within the county. Additional traffic was also incurred in the surrounding counties (e.g., Marshall County, Coffee County, Rutherford County, and Moore County) and produced about 200 tons of CO_2e annually in these counties.

Figure 3: VMT and CO_2e of Switchgrass Transportation to the Conversion Facility in Related Counties in Central Tennessee



CONCLUSIONS

Driven by the increasing interests in the development of advanced biofuel in the U.S., the efficiency of the supply chains providing biomass feedstock to biorefineries is under scrutiny. In addition, the potential environmental impacts of feedstock transportation have generated increased attention given the potential increases in traffic on the current road system. This study estimates the supply chains' cost and hauling emissions of two feedstocks (switchgrass and biomass sorghum) in east, central, and west Tennessee. A spatially-oriented mathematical programming model utilizing crop and pasture land availability, yield, the real road network, and other data was used to determine the optimal location of a single-feedstock 50-MGY conversion facility, associated feedstock draw area, and delivery routes on the road network. Based on the output of the cost minimization from the model, the emissions of additional traffic from feedstock transportation in each region is simulated using the U.S. EPA's emissions modeling tool.

Our results indicate that the cost of biomass feedstock supply chains is influenced by the yield of the feedstock, available crop land, and opportunity cost of converting traditional crops to energy crops. From an economic standpoint, switchgrass is found to be more feasible than biomass sorghum for cellulosic biofuel production in Tennessee. Significantly higher supply chain costs of biomass sorghum are primarily driven by its production cost. The inputs required to produce an annual crop (biomass sorghum) are more than for a perennial grass (switchgrass). Furthermore, limited availability of crop land and less fertile soil, particularly in east Tennessee, generate a more dispersed feedstock draw area and higher transportation cost.

Additional truck traffic from biomass feedstock hauling produces more emissions in the study region. Comparing trucking emissions, hauling biomass sorghum to the conversion facility created significantly more GHG emissions than delivering switchgrass. The higher emission level was related to substantial vehicle travel miles associated with biomass sorghum deliveries resulting from the larger feedstock draw area. Hauling switchgrass to the optimal site in central Tennessee produces the least emissions. Our findings, in line with Jäppinen et al. (2013), suggest that availability of land types and the geographically diverse landscape across the state are influential to the supply chains' cost and feedstock transportation emissions for biomass feedstock. Thus, spatial characteristics will be important elements when designing a commercial-scale bioenergy sector in the regional development plan.

References

Bigazzi, A.Y., and M.A. Figliozzi. "Congestion and Emissions Mitigation: A Comparison of Capacity, Demand, and Vehicle Based Strategies." *Transportation Research Part D: Transport and Environment* 17, (2012): 538-547.

Cundiff, J.S., N. Dias, and H.D. Sherali. "A Linear Programming Approach for Designing A Herbaceous Biomass Delivery System." *Bioresource Technology* 59, (1997): 47–55.

Ekşioğlu, S.D., S. Zhang, S. Li, S. Sokhansanj, and D. Petrolia. "Analyzing the Impact of Intermodal Facilities to the Design of the Supply Chains for Biorefineries." *Transportation Research Record* 2191, (2010): 144–51.

Freppaz, D., R. Minciardi, M. Robba, M. Rovatti, R. Sacile, and A. Taramasso. "Optimizing Forest Biomass Exploitation for Energy Supply at A Regional Level." *Biomass and Bioenergy* 26, (2004): 15-25.

Fürst, E., and P. Oberhofer. "Greening Road Freight Transport: Evidence from an Empirical Project in Austria." *Journal of Clean Production* 33, (2012): 67-73.

Ghafghazi, G., and M. Hatzopoulou. "Simulating the Environmental Effects of Isolated and Area-wide Traffic Calming Schemes Using Traffic Simulation and Microscopic Emission Modeling." *Transportation* 41, (2014): 633-649.

Guo, R., and Y. Zhang. "Exploration of Correlation Between Environmental Factors and Mobility at Signalized Intersections." *Transportation Research Part D: Transport and Environment* 32, (2014): 24-34.

Hess, J.R., C.T. Wright, and K.L. Kenney. "Cellulosic Biomass Feedstocks and Logistics for Ethanol Production." *Biofuels, Bioproducts and Biorefining* 1(3), (2007):181-190.

Jager, H.I., L.M. Baskaran, C.C. Brandt, E.B. Davis, C.A. Gunderson, and S.D. Wullschleger. "Empirical Geographic Modeling of Switchgrass Yields in the United States." *GCB Bioenergy* 2, (2010): 248–257.

Jäppinen, E., O.J. Korpinen, and T. Ranta. "Effects of Local Biomass Availability and Road Network Properties on the Greenhouse Gas Emissions of Biomass Supply Chain." *ISRN Renewable Energy* 2011, Article ID 189734, (2011): 1-6.

Jäppinen, E., O.J. Korpinen, and T. Ranta. "The Effects of Local Biomass Availability and Possibilities for Truck and Train Transportation on the Greenhouse Gas Emissions of a Small-Diameter Energy Wood Supply Chain." *Bioenergy Research* 6, (2013): 166-177.

Khachatryan, H., E.L. Jessup, and K. Casavant. "Derivation of Crop Residue Feedstock Supply Curves Using Geographic Information Systems." *Journal of the Transportation Research Forum* 48, (2009): 5-21.

Kumar, A., S. Sokhansanj, and P.C. Flynn. "Development of a Multicriteria Assessment Model for Ranking Biomass Feedstock Collection and Transportation Systems." *Applied Biochemistry and Biotechnology* 129, (2006): 71–87.

Larson, J.A., T.E. Yu, B.C. English, K.L. Jensen, Y. Gao, and C. Wang. "Effect of Outdoor Storage Losses on Feedstock Inventory Management and Plant-gate Cost for a Switchgrass Conversion Facility in East Tennessee." *Renewable Energy* 74, (2015): 803-14.

Larson, J.A., T. Yu, B.C. English, D.F. Mooney, and C. Wang. "Cost Evaluation of Alternative Switchgrass Producing, Harvesting, Storing, and Transporting Systems and their Logistics in the Southeastern US." *Agricultural Finance Review* 70, (2010): 184-200.

Mafakheri, F., and F. Nasiri. "Modeling of Biomass-to-Energy Supply Chain Operations: Applications, Challenges and Research Directions." *Energy Policy* 67, (2014): 116–126.

Mahmudi, H., and P.C. Flynn. "Rail vs. Truck Transport of Biomass." *Applied Biochemistry and Biotechnology* 129, (2006): 88–103.

Marvin, W.A., L.D. Schmidt, S. Benjaafar, D.G. Tiffany, and P. Daoutidis. "Economic Optimization of a Lignocellulosic Biomass-to-Ethanol Supply Chain." *Chemical Engineering Science* 67, (2012): 68-79.

Mooney, D.F., J.A. Larson, B.C. English, and D.D. Tyler. "Effect of Dry Matter Loss on Profitability of Outdoor Storage of Switchgrass." *Biomass and Bioenergy* 44, (2012): 33-41.

Morrow, W.R., W.M. Griffin, and H.S. Matthews. "Modeling Switchgrass Derived Cellulosic Ethanol Distribution in the United States." *Environmental Science and Technology* 40, (2006): 2877–86.

Mukherjee, A., B. Stawowy, and D. Cass. "Project Emission Estimator: Tool for Contractors and Agencies for Assessing Greenhouse Gas Emissions of Highway Construction Projects." *Transportation Research Record* 2366, (2013): 3-12.

Papson, A., S. Hartley, and K. Kuo. "Analysis of Emissions at Congested and Uncongested Intersections with Motor Vehicle Emission Simulation 2010." *Transportation Research Record* 2270, (2012): 124-131.

Roni, M.S., S.D. Ekşioğlu, E. Searcy, and J.J. Jacobson. "Estimating the Variable Cost for High-Volume and Long-Haul Transportation of Densified Biomass and Biofuel." *Transportation Research Part D: Transport and Environment* 29, (2014): 40–55.

Rooney, W.L., J. Blumenthal, B. Bean, and J.E. Mullet. "Designing Sorghum as a Dedicated Bioenergy Feedstock." *Biofuels, Bioproducts and Biorefining* 1, (2007): 147–57.

Sharma, B., R. Ingalls, C. Jones, and A. Khanchi. "Biomass Supply Chain Design and Analysis: Basis, Overview, Modeling, Challenges, and Future." *Renewable and Sustainable Energy Reviews* 24, (2013): 608-627.

Tao, F., Q. Shi, and L. Yu. "Evaluation of Effectiveness of Coordinated Signal Control in Reducing Vehicle Emissions During Peak Hours Versus Nonpeak Hours." *Transportation Research Record* 2233, (2011): 45-52.

Tembo, G., F.M. Epplin, and R.L. Huhnke."Integrative Investment Appraisal of a Lignocellulosic Biomass-to-Ethanol Industry." *Journal of Agricultural and Resource Economics* 28, (2003): 611-633.

Tiller, K. "Tennessee Case Study in Full-scale Development and Integration of Switchgrass Feedstocks with Biorefinery Operations: Genera Energy and UT Biofuels Initiative." *Industrial Biotechnology* 7, (2011): 357-364.

Turhollow, A., R. Perlack, L. Eaton, M. Langholtz, C. Brandt, M. Downing, L. Wright, K. Skog, C. Hellwinckel, B. Stocks, and P. Lebow. "The Updated Billion-ton Resource Assessment." *Biomass and Bioenergy* 70, (2014): 149-164.

Tyner, W.E., and C.W. Rismiller. "Transportation Infrastructure Implications of Development of a Cellulosic Biofuels Industry for Indiana." *Journal of the Transportation Research Forum* 49, (2010): 95-112.

University of Tennessee. Extension Maps and Locations. 2014. https://extension.tennessee.edu/Pages/Office-Locations.aspx. University of Tennessee Institute of Agriculture, *Field Crop Budgets for 2011*, E12-4115. 2011.

U.S. Department of Agriculture, National Agricultural Statistics Service. *Crop Values: 2011 Summary*. February 2012.

U.S. Department of Agriculture, National Agricultural Statistics Service. *CropScape − Cropland Data Layer Database.* 2011. Available at: http://nassgeodata.gmu.edu/CropScape.

U.S. Department of Agriculture. Nature Resources Conservation Service. *Soil Survey Geographic (SSURGO) Database*. 2014. Availble at: http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053627

U.S. Department of Energy. *U.S. Billion-ton Update: Biomass Supply for a Bioenergy and Bioproducts Industry*. Perlack, R.D. and B.J. Stocks (Leads). Oak Ridge National Laboratory, ORNL/ TM-2011/224. August 2011.

U.S. Environmental Protection Agency. *Motor Vehicle Emission Simulator (MOVES) User Guide for MOVES2010b*. EPA-420-B-12-001b. June 2012.

Vallamsundar, S., and J. Lin. "MOVES versus MOBILE: Comparison of Greenhouse Gas and Criterion Pollutant Emissions." *Transportation Research Record* 2233, (2011): 27-35.

Wright, L., and A. Turhollow. "Switchgrass Selection as a 'Model' Bioenergy Crop: A History of the Process." *Biomass and Bioenergy* 34, (2010): 851-868.

Xie, Y., M. Chowdhury, P. Bhavsar, and Y. Zhou. "An Integrated Modeling Approach for Facilitating Emission Estimations of Alternative Fueled Vehicles." *Transportation Research Part D: Transport and Environment* 17, (2012): 15-20.

APPENDIX

The cost of energy crops at the conversion facility gate is defined as:

(1) $TC_F = C_{opportunity} + C_{production} + C_{harvest} + C_{storage} + C_{transportation}$

where TC_F is the total economic cost (\$) of the biomass supply chain, and $C_{opportunity}$, $C_{production}$, $C_{harvest}$, $C_{storage}$, and $C_{transportation}$ are opportunity costs from land conversion, production cost, harvest cost, storage cost, and transportation cost of energy crops, respectively. Table A1 summarizes the definition of the parameters and variables used in the equations.

The opportunity cost for energy crops (either switchgrass or biomass sorghum) production is defined as the profit of previous crop in equation (2). If the net revenue of previous crop is less than the county-level land rent, the land rent is used as the opportunity cost instead. The production cost in equation (3) comprise both amortized establishment cost of the first year and an annual maintenance cost. Harvest cost factor (Sigma) in equation (4) includes equipment ownership cost, operating cost, operating interest cost, and labor cost. Similarly, cost of storage material, equipment ownership, storage operation, operating interest, and labor are considered in the storage cost factor (γ) in equation (5). The transportation cost factor, θ, in equation (6) considers loading and unloading costs, labor costs, and machinery costs.

(2) $$C_{opportunity} = \begin{cases} \sum_{ip}\left(\frac{Price_{ip} * Yield_{ip} - PC_{ip}}{Yield_i^{swi}} * XC_{ip}\right), \text{if } (Price_{ip} * Yield_{ip} - PC_{ip}) - LR_{ip} \geq 0 \\ \sum_{ip}\left(\frac{LR_{ip}}{Yield_i^{swi}} * XC_{ip}\right), \quad \text{if } (Price_{ip} * Yield_{ip} - PC_{ip}) - LR_{ip} < 0 \end{cases}$$

(3) $C_{production} = \sum_{ip}\left(\frac{\text{Est+AM}}{Yield_i^{swi}} * XC_{ip}\right)$

(4) $C_{harvest} = \sum_{ip}\left(\frac{\text{Sigma}_i}{Yield_i^{swi}} \times XC_{ip}\right)$

(5) $C_{storage} = \sum_{mipt} \gamma_{it} * NXS_{mipt}$

(6) $C_{transportation} = \sum_i \theta_i \times \frac{\sum_{mp} XTN_{mip} + \sum_{mpt} XTO_{mipt}}{1 - DMLT}$

Subject to:

Land use constraints:

(7) $A_{ip} \leq PAS_p \times aa_{ip}, \forall\, i, p$

(8) $XC_{ip} \leq Yield_i^{swi} \times A_{ip}, \ \forall\, i, p$

Harvest constraints:

(9) $XC_{ip} - \sum_m XH_{mip} \geq 0, \ \ \forall\, i, p$

(10) $\sum_{i,p,} XH_{mip} = \frac{CapUnit}{\lambda} \times rateava_m, Dec \leq m \leq Feb \ \& \ \forall\, m$

(11) $XH_{mip} = 0, \ March \leq m \leq Oct \ \forall\, m, i, p$

(12) $Numb_m{}^{\kappa} \times avehour_m - \sum_{i,p}(mtb_i{}^{\kappa} \times AH_{mip}) \geq 0\ ,\ \forall\, m$

Harvest-inventory balance constraints:

(13) $\sum_t^2 NXS_{mipt} = XH_{mi} - \frac{XTN_{mip}}{1-DMLT}\ ,\ Nov\ \leq m \leq Feb\ \&\ \forall\, m, i, p$

(14) $XS_{(m+1)ipt} = (1 - DMLS_{mt}) \times XS_{mipt} +\ NXS_{(m+1)ipt}\ , Nov\ \leq m \leq Feb\ \&\ \forall\, m, i, p, t$

(15) $XS_{(m+1)ipt} = (1 - DMLS_{mt}) \times XS_{mipt} - \frac{XTO_{(m+1)ipt}}{1-DMLT},\ Mar \leq m \leq Oct\ \forall\, m, i, p, t$

(16) $XS_{mipt} = 0\ ,\ m = Oct\ \&\ \forall\, m, i, p, t$

Demand constraints

(17) $\lambda(\sum_{i,p} XTN_{mip} + \sum_{i,p,t} XTO_{mipt}) = Dd_m\ ,\ \forall\, m$

Table A1. Definitions of Subscripts, Parameters and Variables

	Unit	Definition
Subscripts		
i		locations of energy crop production field
m		month
p		crops (hay & pasture, corn, soybean, wheat)
t		storage protection method
k		type of machinery (tractor, mower, loader, rake)
Parameters		
Price_{ip}	\$/unit	traditional crop price
Yield_{ip}	acre/unit	tradition crop yield
PC_{ip}	\$/acre	production cost of traditional crop
$Yield_i^{swi}$	d ton/acre	yield for energy crop in each hexagon
LR_{ip}	\$/acre	land rent of traditional crop
Est	\$/acre	Establishment cost in the first year
AM	\$/acre	Annual maintenance cost
Sigma_i	\$/acre	cost of harvesting energy crop
γ_{it}	\$/d ton	cost of storing energy crop
θ_i	\$/d ton	cost of transporting energy crop from field to facility
aa_{ip}	acre	cropland available in each hexagon for each crop
$CapUnit$	gallon/year	annual capacity of a conversion facility
λ	gallon/d ton	energy crop-ethanol conversional rate
$rateava_m$	%	ratio of working hours in each month to total
$avehour_m$	hour	average working hours of machinery in each month
mtb_i	hour/acre	machine time per acre for each machinery
PAS_p	%	maximum percent of land converted
$DMLT$	%	dry matter loss during transportation
$DMLS_{mt}$	%	dry matter loss during storage
Dd_m	gallon/month	monthly demand for ethanol
Variables		
A	acre	ha of energy crop produced annually
AH	acre	ha of energy crop harvested monthly
XC	d ton	dry weight of energy crop produced annually
XH	d ton	dry weight of energy crop harvested monthly
XTN	d ton	dry weight of energy crop transported directly to the facility after harvest
NXS	d ton	dry weight of energy crop newly stored monthly from November to February
XS	d ton	dry weight of energy crop stored monthly from November to October
XTO	d ton	dry weight of energy crop transported from storage to the facility
$Numb$	unit	number of equipment used in harvest

Yu *is an associate professor in the Department of Agricultural & Resource Economics at the University of Tennessee. He received an M.Sc. in economics from Iowa State University and a Ph.D. in agricultural economics from Texas A&M University. His research focuses on agricultural logistics, bioenergy economics, and the nexus of trade, transportation, and the environment.*

Larson *is professor and director of graduate studies in the Department of Agricultural & Resource Economics at the University of Tennessee. He received a Ph.D. in agricultural economics from Oklahoma State University. His research focuses on production economics, farm management, and risk management. His research interests include the economics of biomass feedstock production at the farm and supply chain levels.*

English *is a professor in the Department of Agricultural & Resource Economics at the University of Tennessee. He received an M.Sc. in agricultural economics from New Mexico State University and a Ph.D. in agricultural economics from Iowa State University. His research focuses on agricultural production, bioenergy economics, and the nexus of agricultural production, resource needs, and the environment.*

Fu *is a professor in the Department of Civil and Environmental Engineering at the University of Tennessee. He received an M.Sc. in environmental engineering and water resources from the University of California at Los Angeles and a Ph.D. in civil engineering from North Carolina State University. His research focuses on air quality, climate science and its impacts, energy, transportation and the environment.*

Calcagno *is a post-doc research associate in the Department of Civil & Environmental Engineering at the University of Tennessee. He received a Ph.D. in civil and environmental engineering from the University of Tennessee. His research focus is on vehicle emissions.*

Wilson *is a GIS specialist in the Department of Agricultural & Resource Economics at the University of Tennessee. He has nearly 20 years of experience with geographical information systems and software development. His research has focused on developing spatial models for assessing feedstock availability, transportation of biomass, and potential locations for biorefineries. Other areas of spatial analysis include agricultural land use change, crop yield assessment, soil survey analysis, and weather patterns.*

Welfare Measures to Reflect Home Location Options When Transportation Systems are Modified

by Shuhong Ma and Kara M. Kockelman

Transportation system improvements do not provide simply travel time savings, for a fixed trip table; they affect trip destinations, modes, times of day, and, ultimately, home and business location choices. This paper examines the welfare (or willingness-to-pay) impacts of system changes by bringing residential location choice into a three-layer nested logit model to more holistically anticipate the regional welfare impacts of various system shifts using logsum differences (which quantify changes in consumer surplus). Here, home value is a function of home price, size, and accessibility; and accessibility is a function of travel times and costs, vis-à-vis all mode and destination options. The model is applied to a sample of 60 Austin, Texas, zones to estimate home buyers' welfare impacts across various scenarios, with different transit fares, automobile operating costs, travel times, and home prices.

Results suggest that new locators' choice probabilities for rural and suburban zones are more sensitive to changing regional access, while urban and central business zone choice probabilities are more impacted by home price shifts. Automobile costs play a more important role in residential location choices in these simulations than those of transit, as expected in a typical U.S. setting (where automobile travel dominates). When generalized costs of automobile travel are simulated to rise 20%, 40%, and 60% (throughout the region), estimated welfare impacts (using normalized differences in logit logsum measures) for the typical new home buying household (with $70,000 in annual income and 2.4 household members) are estimated to be quite negative, at -$56,000, -$99,000, and -$132,000, respectively. In contrast, when auto's generalized costs fall everywhere (by 20%, 40%, and then 60%), welfare impacts are very positive (+$74,000, $172,500, and $320,000, respectively). Such findings are meaningful for policymakers, planners, and others when anticipating the economic impacts of evolving transportation systems, in the face of new investments, rising travel demands, distance-based tolls, self-driving vehicles, and other changes.

INTRODUCTION

An understanding and consideration of residential location choice is fundamental to behavioral models of land use and, ultimately, travel demand (Bina et al. 2006) and community welfare. Residential location choice decisions are influenced by a host of quantifiable and unquantifiable factors (e.g., Rossi 1955), including home attributes (like home price, size, and age), travel costs (or/and travel times), and access (to freeways and transit stations, schools, jobs, parks and shopping centers), and household demographics (like income and the presence of children) (Habib and Kockelman 2008). While challenging in execution, home (and business) location models are very valuable to the regional, long-run transportation planning process and to land use-transport policymaking (Ommere et al. 1999; Pinto 2002; Hollingworth and Miller 1996; Zhou and Kockelman 2011).

The location choice model presented here relies on the method of logsum differences[1] under a three-layer nested logit (NL) structure (for location, destination, and mode choice), with systematic utility modeled as a combination of home price, home size, and neighborhood accessibility. By making assumptions about home price, access attributes, travel cost and travel time sensitivity, and all model parameters, one can compute choice probabilities for each alternative setting and estimate welfare changes across scenarios (from equivalent variation or willingness-to-pay values), as experienced by households looking to locate in a region. While property valuation research has long examined the price impacts of local travel system changes (Mohring 1961, Allen 1981, Nelson 1982, Bajic 1983, Voith 1991, TenSiethoff and Kockelman 2002), the approach pursued here takes the question of transportation improvements' welfare impacts to a whole new level, using direct measures of welfare economics across multiple and often competing costs shifts (using differences in logsums [Ben-Akiva and Lerman 1985], normalized to reflect dollar values, much like a willingness-to-pay metric). The expected maximum utility of mode plus destination plus location and home choices depend on travel times and travel costs to all potential destinations. This approach is consistent with prior research, as cited in the paper (e.g., locators/movers pay much attention to work and school travel times, as well as access to major freeways and transit lines), but this paper's recognition of the location choice behavior is very novel.

Accessibility has long been theorized and proven a major determinant of residential location choice behavior (Alonso 1964, Zondag and Pieters 2006, and Lee and Waddell 2010), and some existing literature helps to illustrate its influence on home location choice. However, a more detailed and nuanced analysis is needed to explore the relationships among travel costs and times, accessibilities, and home-buyer/residential locator benefits. Moreover, the influence of each factor on house buyer benefits and the sensitivity of these benefits with changes in input variables merit examination. This work offers such a closer look, which should be of interest to policymakers and planners when seeking methods for more rigorous and defensible methods of evaluating project and policy impacts. This work begins with a description of existing, related literature, followed by a description of methods and model specifications, regional examples, and key findings.

BACKGROUND

Home location choice has been modeled in a variety of ways. Many rely on stand-alone choice models (e.g., NL, multinomial logit [MNL], and mixed logit specifications) for individual households, in isolation or as part of a larger land use model. For regional-scale modeling, many past models have kept track of household (and job) count totals at the zonal (aggregate) level. For example, Ben-Akiva and Bowman (1998) developed an integrated nested logit model for Bostonians' residential location choices, along with members' activity and travel schedules. They found that the NL structure did not fit the data quite as well as a work-trip-based comparison model. Lee and Waddell (2010) devised a two-layer NL model (decision to move or to stay, followed by location choice) and confirmed the model's applicability with a case study in Seattle, Washington. Zhou and Kockelman (2011) explored a series of models for household and firm location choice around Austin, Texas, and found that that a three-layer NL structure, with location choice nested within home type choice, provided reasonable estimates. MNL models have also been popular. For example, Zhou and Kockelman (2008a) used such models to simulate location choices for three different household types using survey data of recent home buyers in Austin, Texas. They found that working households evaluate commute time differently when choosing their home location, with higher home-price-to-income ratios having a strong negative impact on their choice probabilities.

Other papers have examined residential location choice within a larger land use framework. Dang et al. (2011) established a household residential location choice model for a mono-centric city to quantitatively explore the evolution of urban residential housing consumption based on data from a survey in Beijing, China. Findings indicate that the balance between commuting costs and housing costs is key in the residential location selection process, similar to findings from Yang (2006) and Zhou and Kockelman (2008b). Zhang and Kockelman (2015) developed a spatial general equilibrium model to explore the endogenous relations between urban sprawl, job decentralization, and traffic congestion, and compared the efficiency and welfare impacts of anti-congestion policies.

Results indicate that firms tend to decentralize while households move toward the city center as congestion grows.

To describe the relationship between land-use and residential location choice, many researchers have used an accessibility index (AI) as a parameter. Srour et al. (2002) used different accessibility indices to estimate residential location choice and noted that job accessibility affects residential land values positively in statistically and economically significant ways, with distance to the central business district (CBD) and household head's workplace location playing important roles in residential location predictions. Zondag and Pieters (2006) built a move-stay choice model and a residential location choice model by home type (with data from The Netherlands), and showed that the role of accessibility is significant but small compared with the effect of demographic factors, neighborhood amenities, and dwelling attributes. Lee et al. (2010) proposed a time-space prism (TSP) accessibility measure, and applied it to residential location choice in the Central Puget Sound region. The study confirmed that accessibility is an important factor in residential location choice, with individual-specific work accessibility being the most critical consideration. Bina et al. (2006, 2009) ranked the importance of housing and location attributes (home price, commute time to work, perception of crime rate, attractive neighborhood appearance, commute time to school, and access to major freeways are the top six) by using linear regression models which utilized an accessibility index calibrated from logsums from travel demand models of home-based work trips.

The rule-of-half (RoH) and logsum differences are two typical methods in transport economics to estimate welfare. In the case of modeling home location choice, RoH method cannot be used for the home buyer/mover benefits calculation since there is no added demand (with just one home per household, typically). However, random-utility maximization (RUM) assumptions (where decision-makers are assumed to choose the alternatives that benefit them most) are suitable for developing a location choice model, and the logsum differences can be used to determine home buyer/mover welfare under the assumption that each household chooses its home location to maximize its utility function involving all parameters considered. McFadden (1978, 1981) used logsum differences based on RUM assumptions (with Gumbel-type error terms) to estimate user benefits and losses when their travel (or others' travel) context changes. Many applications using logsums as an evaluation measure have been conducted in Europe, the U.S., and other countries for policy (decision) making, land use modeling, and road (congestion) toll demand prediction (Jong et al. 2005; EXPEDITE Consortium, 2002; Odeck et al. 2003, Castiglione et al. 2003; Kalmanje and Kockelman 2004). Logsum differences have also been used to evaluate land-use strategies in a climate change context. Geurs et al. (2010) evaluated data from The Netherlands and showed that such access benefits (with user benefits calculated using logsum difference following access changes) from land-use policy strategies can be quite large compared with investment programs for road and public transport infrastructure, largely due to changes in trip production and destination utility, which are not measured in the standard rule-of-half benefit measure.

While much research has been conducted on home location choice analysis, previous studies typically focus on what and how the factors affect the home buyer's/mover's decision. Additionally, the majority of home location choice studies are specific cities, districts, or zones based on SP (Stated Preference) or RP (Revealed Preference) datasets, under the assumption that people choose the home that enables them to achieve the largest utilities. The change in house buyer's utilities and benefits needs to be examined more deeply in a welfare context. Adding to the previous research on location choice, this paper presents a three-layer NL model with destination-mode choice nested in location choice, using logsum differences to estimate household welfare.

METHODOLOGY

As discussed above, home location choices regularly represent a trade-off between housing type (including variables of home price, size, and age) and site accessibility, with income, household size, presence of children, job locations, and other demographic factors also playing roles (Zondag and Pieters 2006; Dang et al. 2011; Zhou and Kockelman 2008a, 2011; Habib and Kockelman 2008). Based on random-utility theory, logit-type models (McFadden 1978) have been widely used to explore this important household choice. The MNL framework has been the most common approach (Tu and Goldfinch 1996; Hunt et al. 1994; Sermons and Koppelman 2001; Zhou and Kockelman 2008a, 2008c), with the assumption that all unobserved factors (among competing home alternatives) are uncorrelated and homogeneous. NL models have also been applied here, often to predict both home location and home size (Habib and Kockelman 2008; Zondag and Pieters 2006; Lee and Waddell 2010) or activity-based accessibility (Ben-Akiva and Bowman 1998).

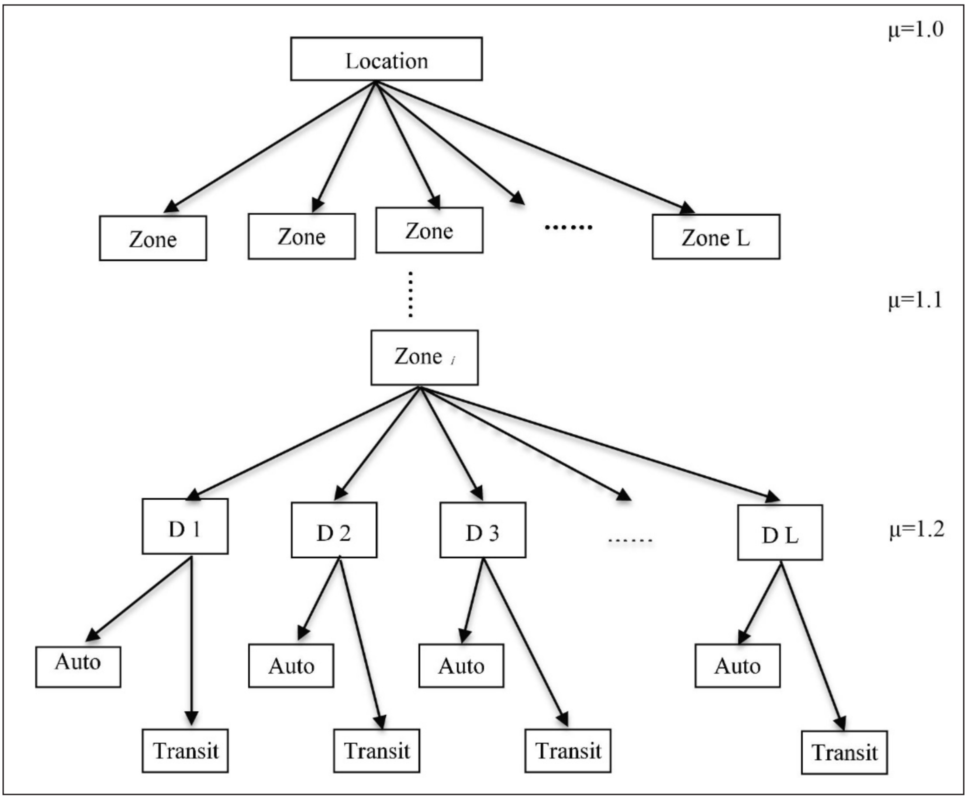
This study relies on both MNL and NL equations, with systematic utility values that combine home price, home size, and logsum accessibility metrics to specify (and then simulate) location choice behaviors. The study then uses logsum differences to quantify the welfare effects of transportation system changes, along with other model variations. These methods, model structure, and applications are described below.

Model Structure for Location Choice

In evaluating home location choice, it is useful to first determine the most important aspects and attributes of that choice, such as home price, number of bedrooms, number of living areas, home age, lot size, travel time to work and recreation, and so on. This paper uses each home's price, size, and nested logsum-based accessibility metric (shown later, in Eq 7) as the critical choice attributes (consistent with recent research[2]), and employs an MNL specification to estimate the probability of choosing each location. A common practice in classifying household location is to use census tracts, zip codes, or traffic analysis zones (TAZs) (McFadden 1981; Habib and Kockelman 2008; Bina and Kockelman 2009) as the location choice set. This model assumes the region of study is divided into L location zones, with each zone serving as a location alternative, and as a potential trip destination for the logsums that characterize the origin zone's accessibility. Since home-location access is based on a two-level logsum (for destination and mode choices), the home-choice model specification becomes a three-layer nested-logit model structure, as illustrated in Figure 1.

There are three distinct choice dimensions being modeled here, so the structure reflects three embedded nests. This NL specification allows clusters of similar options to exhibit correlated error terms (Ben-Akiva and Lerman 1985). From top to bottom are location choice, destination choice, and finally, mode choice. The top level is the MNL home location zone model, where the probability of each household choosing to reside in a zone is computed as a function of home price, home size, accessibility, and other variables. The middle level is a destination choice model (for any single trip) where people choose a destination for their typical trip to other zones (including origin zone) based on the logsums of mode choices (lowest level). Lastly, the lowest level of the NL structure is a mode choice model (for the trip between zones) by destination that accounts for the generalized cost (travel cost and travel time) of each mode (only auto and public transit [bus] are considered here). Reasonable behavioral parameter values, as tested by Lemp and Kockelman (2008), were used here to characterize preferences. Figure 1 also shows the associated scale parameters (the μ values).

Figure 1: Nested Logit Model Structure on Home Location Choice



Logsum Method for User Benefits Estimation

As discussed in the literature review, use of logsum differences is a relatively more recent approach for anticipating consumer surplus changes than the more traditional rule-of-half method.[3] It also comes with much more of a disaggregate perspective on choice dynamics, and requires the presence of competing choice alternatives (versus a single demand market, for example, as is common in more traditional rule-of-half applications). Logsum differences have been used for welfare analyses of land use and environmental policies and in home location choice studies (USDOT 2004; Geurs et al. 2010; Lee et al. 2010). When using a logit model with RUM assumptions (i.e., that people anticipate and select the alternative that offers them maximum utility), consumer surplus changes are calculated as the difference between the expected consumer surplus levels E(CS_n) before and after the change (i.e., across scenarios), reflecting all alternatives, as follows:

(1) $\Delta E(CS_n) = 1 / \alpha_n)[\ln\sum_i e^{V^1_{ni}}) - \ln(\sum_i e^{V^0_{ni}})], \forall n,i$

where superscript 0 and 1 refer to before and after the change, α_n represents the marginal utility of income for person n (can also be expressed as dU_n/dY_n, where Y_n is the income of person n), U_n is the overall utility for person n, V_{ni} is the representative utility (or indirect utility, often expressed as a function of travel time and cost) for person n to experience alternative i. Thus, U_{ni} is the overall utility for person n choosing alternative i, and V_{ni} denotes the systematic or representative utility for person n choosing alternative i.

In this model, determining the probabilities of a home buyer choosing each location alternative is a key step. These probabilities are estimated by evaluating the characteristics of each alternative in order to assess an indirect utility associated with the alternative. In an MNL model, this may be expressed using Eqs (2) and (3).

$$(2) \quad P_i = e^{V_i} / \sum_{i=1}^{K} e^{V_i}$$

$$(3) \quad V_i = \beta_1 \cdot X_{i1} + \beta_2 \cdot X_{i2} + \beta_3 \cdot X_{i3} + \cdots + \beta_n \cdot X_{in}$$

where P_i is the probability of a user/consumer choosing alternative i from alternative choice set K; V_i is the representative utility(indirect utility) of alternative i, which is usually a linear function of attributes X_i (as shown in equation 3); and β_i is utility coefficient for each attribute.

MODEL SPECIFICATION

Some assumptions and simplifications are made in this NL model structure. For the top level, the sole variables assumed here to affect the location choice are accessibility, home price, and home size. In the second choice stage, the only variables affecting destination choice probabilities are the logsums for (auto and transit) mode options. At the bottom level, the only variables assumed to affect mode choices are travel time and travel cost (along with alternative-specific constants, or ASCs, for each mode).

Based on the previous discussion of the NL model structure and calculation of logsum differences, key modeling equations (for generalized trip costs, systematic utilities, and inclusive value parameters of the nested choices and choice probabilities) are as follows:

$$(4) \quad GC_{ldm} = VOTT \cdot TIME_{ldm} + COST_{ldm} \qquad \text{Generalized costs}$$

$$(5) \quad V_{ldm} = ASC_m - GC_{ldm} \qquad \text{Systematic utilities}$$

$$(6) \quad \Gamma_{ld} = \frac{1}{\mu_1} \ln[\exp(\mu_1 \cdot V_{ld,transit}) + \exp(\mu_1 \cdot V_{ld,Auto})] \qquad \text{Expected max. utilities}$$

$$(7) \quad AI_l = \Gamma_l = \frac{1}{\mu_2} \ln[\exp(\mu_2 \cdot \Gamma_{l,d_1}) + \exp(\mu_2 \cdot \Gamma_{l,d_2}) + \ldots + \exp(\mu_2 \cdot \Gamma_{l,d_n})] \quad \text{Accessibility indices}$$

Each trip's generalized cost (GC_{ldm}) is a linear function of travel time (*TIME*) and travel cost (*COST*) – which includes any tolls plus (other) operating costs − between each (potential) home zone l (1:L) and each destination zone d, via mode m (for transit and auto), with all values of travel time (*VOTT*) assumed to be \$12/hr here (consistent with FHWA guidance [2015] and Lemp and Kockelman's [2011] simulations). The systematic utilities (V_{ldm}) of these alternatives (shown in Eq 5 and 6) are measured in dollars, and include the appropriate mode's ASC (assumed to be 0 for the auto mode and -1.1 for transit, as used by Kockelman and Lemp [2011]). The expected utility of a destination zone, d, as shown in Eq. 6, lacks an attractiveness factor. Usually, destination zones differ in the number of work, shopping, recreation, and other opportunities they offer (though TAZ boundary decisions often have a target population or population range in mind, so they are often roughly equivalent in terms of household trip generation). To avoid introducing land use effects, from variations in jobs (by type) or other attraction features, the models used here presume equal attractiveness, for household trip making, across all 60 zones, ceteris paribus. Travel times and costs vary, however, by mode and to each destination zone, given a starting (home) zone. So destination zones are not equally attractive once travel costs are taken into account.

Equation 7's accessibility metric, AI_l, is the logsum, Γ_l, which denotes the inclusive value or expected maximum utility of the two-level (destination and mode) choices available to a home zone l. This term requires no normalizing coefficient, since the utilities, V, are already measured in dollars. Finally, at top level of the effectively three-level NL framework, the household's expected choice probability of each location is as follows:

$$(8)\quad \Pr_l = \frac{\exp(\mu_3 . U_l)}{\sum_{l=1}^{L} \exp(\mu_3 . U_l)}$$

$$(9)\quad U_l = \alpha_1 \cdot P_l + \alpha_2 \cdot SFl + \alpha_3 \cdot AI_l$$

where Pr(.) represents the probability of a particular choice (home location choice); U denotes the expected maximum utility of the top level alternative; SF denotes the square footage (home size); and P denotes the home price. The α_1, α_2, and α_3 are indirect utility slope parameters on home price, home size, and accessibility, which vary with each potential home zone l. In the following example, the values of α_1 and α_2 were calculated using Zhou and Kockelman's (2011) work,[4] and α_3 was assumed to be the same AI coefficient (0.635) found in Lee and Waddell's (2010) paper, based on a logsum (for work trips) to all destination zones.

μ_1, μ_2, μ_3 serve as the three choice-levels' utility scaling parameters for the mode, destination, and location choices. These are the inverse of the logit model's inclusive value coefficients, as defined in Ben-Akiva and Lerman (1985), and they serve as coefficients in the utility expression. Consistent with McFadden's random-utility theory, the scale parameters are usually assumed to fall from the lowest to the highest level nest (see, e.g., Kockelman and Lemp 2011[5]). Here, scale parameters of 1.2 (μ_1) in the lowest, 1.1 (μ_2) in the middle nest, and 1.0 (μ_3) in the upper level nest were assumed. These are falling (from the lowest to the highest level nest), and the inverse of each lies between 0 and 1, consistent with RUM assumptions (Ben-Akiva and Lerman 1985).

Estimates of consumer surplus changes (ΔCS) for each scenario (as compared with the starting or base case setting) were computed as well. Normalized logsums of systematic utilities are used here as the basis for estimating those welfare changes, as follows:

$$(10)\quad \Delta CS_n = \frac{1}{\alpha_n} \{\ln[\sum_l \exp(\mu_3 U_l^1)\text{-}\ln[\sum_l \exp(\mu_3 U_l^0)]\}$$

Here, CS can be measured between any two scenarios, but this paper looks primarily at the change in consumer surplus as measured in reference to the base scenario. Here, α_n represents the marginal utility of income for person n, assumed to be the reciprocal of α_1's absolute value, so all α_n are set to \$10,000/0.0357 = \$280,112.

NUMERICAL EXAMPLES

In order to fully appreciate the consumer surplus changes (home buyer welfare effects) as a result of the changes in access, home price, and other factors, the NL model was applied to a variety of scenarios, which vary. For example, the generalized costs of either mode, auto's operating cost and travel time, home prices, and VOTT. The travel time and cost data used in this example come from TAZ-based skim files[6] of Austin, Texas' Capital Area Metropolitan Planning Organization (CAMPO) for a three-county network in the year 2000. Sixty (60) of the original 1,074 TAZs were strategically selected as a representative sample of the larger region's location alternatives. Therefore, the AI of one zone is an average access from its zone to the other 1,073 zones and can be calculated using Eq (7).

Table 1 shows the types and distribution of these 60 zones, which reflect four types of land use: rural, suburban, urban, and central business district (CBD) zones (according to CAMPO definitions). Here, CBD zones are assumed to have the highest home prices and rural zones the lowest, due to land-rent increases typical of more central/accessible locations. For simplicity, the home prices are assumed to be \$200,000, \$300,000, \$600,000, and \$1,000,000 in the rural, suburban, urban, and CBD zones (not far from Austin's actual home prices.) Similarly, home sizes are assumed to fall with increased density, with 3,000 ft^2, 2,500 ft^2, 2,000 ft^2, and 1,500 ft^2 serving as the interior/built space for rural, suburban, urban, and CBD homes. Accessibility metrics are much harder to guess at, and were estimated as logsums using actual travel times and travel costs between the 60 zones (travel costs referred to here as "fares," for the transit alternative, and reflecting tolls and vehicle operating costs in the case of the automobile[7]). Table 2 shows the main variables and parameters used in the example, and Table 3 shows the base scenario for the 60 zones.

Table 1: Austin's TAZ Sample

		Rural	Suburban	Urban	CBD	Totals
County	**Hays**	4	4	2	0	*10*
	Travis	9	15	12	2	*38*
	Williamson	4	5	3	0	*12*
Totals		*17*	*24*	*17*	*2*	*60*

Under this base scenario, probabilities of location choices are calculated via Equation 8, with the rural and suburban zones' share being larger due to their relatively higher utilities. The shares of residents in the four types of zones are 0.480, 0.400, 0.117, and 0.0026 (for rural, suburban, urban, and CBD in that order). The model also shows that the probability of a household choosing a rural or suburban zone increases greatly with higher AIs. For example, rural zone 4 and suburban zone 37 have relatively high AIs (0.906 and 1.902) within their zone type, and the probabilities of these two zones being chosen (0.0499 and 0.0328) are relatively large; but for urban zones, especially the CBD zones, even zones with very high AIs are unlikely to be chosen (e.g., zone 60 has the highest accessibility [2.934], but the probability of a household choosing this zone is very small [0.0013]). This indicates that the relative desirability of rural and suburban zones is more sensitive to AIs. In other words, network changes that improve or worsen the accessibility of rural and suburban zones have great impacts on households' decisions to locate in these zones, while the choice to locate in urban and CBD zones is less sensitive to such accessibility changes.

Table 2: Variables and Parameters Used

Variable Used	Variable Description	Parameter Values	
Home price (P)	Average home price (10,000$)	α_1	-0.0357
Square footage (SF)	Average interior square footage (1,000ft2)	α_2	1.39
Accessibility (AI)	Logsums of mode-destination analysis based on travel time and travel cost	α_3	0.635
Scale parameter (μ)	Scale parameter for the lowest level	μ_1	1.2
	Scale parameter for the median level	μ_2	1.1
	Scale parameter for the highest level	μ_3	1.0
Alternative specific constants (ASC)	Alternative specific constants for Auto mode		0.0
	Alternative specific constants for Transit mode		-1.1
VOTT	Value of the travel time ($/h)		$12 per hr
Marginal utility of income (α_n)	Marginal utility of income for person *n*	α_n	$280,110

Several other scenarios are also explored to understand effects on home buyer welfare levels. Scenario 1 examines the effect of transit's generalized travel costs by increasing and decreasing GC_{ij} values by 20%, 40%, and 60%. Scenario 2 examines travel time cost effects, while Scenarios 3 and 4 further explore changes in the auto mode, by varying its operations costs and travel times, respectively. Finally, Scenario 5 examines the impact of changing home prices on home buyers' benefits.

Figure 2 shows the corresponding changes in AIs and the changing probabilities with the changes in inputs in these scenarios. Table 4 shows the shares of households selecting each of the four zone types under different scenarios. Finally, Table 5 compares the home buyer welfare across scenarios. It shows how the generalized cost of automobile travel and home prices play key roles in home buyer welfare gains and losses.

When varying the generalized costs of transit, there are almost no changes or very slight changes in each location's AI and probability of being chosen. For example, when all GC_{ij} values are increased 40%, total probabilities of location choices in CBD and urban zones have no change on average, while those in rural and suburban zones only rose an average of 0.0001 and -0.0001. Home buyer welfare change, as estimated using the logsum difference between the Base scenario and Scenario 1, is very small. When all GC_{ij} values are increased 20%, 40%, and 60%, the estimated average-mover welfare changes are computed to be -$30.8, -$42.6, and -$47.7 (as shown in Table 5). However, when all GC_{ij} values are decreased 20%, 40%, and 60%, the corresponding welfare gains are estimated to be $101, $592, and $4,870. The model implies that decreasing transit fares impact home buyer benefits more significantly than increasing fares.

Changes in generalized costs of auto affect home locations' AI and probability more significantly, as in Figure 2(a). Larger spacing between the AI lines implies that AI is quite sensitive to auto's generalized cost. When all GC_{ij} values are increased by 40%, average location choice probabilities in the rural and CBD zones rise by 0.0210 and 0.0002 (from Table 4: 0.5009-0.4800 = 0.0210 and 0.0028-0.0026 = 0.0002), while those in suburban and urban zones drop an average of 0.0197 and 0.0015 (from Table 4: 0.4004-0.3807 = 0.0197 and 0.1171-0.1156 = 0.0015). This may appear inconsistent with intuition: one typically expects higher generalized auto costs to make more central housing locations relatively more accessible and, therefore, relatively more desirable. However, from Equations (4), (5), (8), and (9), one notices how, as GC_{ij} increases, the AI of *each* zone decreases, making AI *differences* between zones smaller, so an overall shift toward less accessible zones can result.

Table 3: Attributes for Home Location Choice and Probabilities in Base Scenario

Zone type	Zone ID	Home price ($10,000)	Home size (1,000ft^2)	AI	Probability	Zone type	Zone ID	Home price ($10,000)	Home size (1,000ft^2)	AI	Probability
1	1	20	3	-0.872	0.0161	2	31	30	2.5	1.230	0.0214
1	2	20	3	0.018	0.0284	2	32	30	2.5	0.995	0.0184
1	3	20	3	-0.098	0.0264	2	33	30	2.5	0.925	0.0176
1	4	20	3	0.906	0.0499	2	34	30	2.5	0.862	0.0169
1	5	20	3	-0.119	0.0260	2	35	30	2.5	1.431	0.0243
1	6	20	3	0.574	0.0404	2	36	30	2.5	0.836	0.0167
1	7	20	3	0.279	0.0335	2	37	30	2.5	1.902	0.0328
1	8	20	3	-0.195	0.0248	2	38	30	2.5	0.958	0.0180
1	9	20	3	0.040	0.0288	2	39	30	2.5	-0.092	0.0092
1	10	20	3	0.166	0.0312	2	40	30	2.5	-0.403	0.0076
1	11	20	3	0.263	0.0332	2	41	30	2.5	1.709	0.0290
1	12	20	3	-0.421	0.0215	3	42	60	2	1.363	0.0040
1	13	20	3	-0.850	0.0164	3	43	60	2	0.985	0.0031
1	14	20	3	0.777	0.0460	3	44	60	2	0.716	0.0026
1	15	20	3	-0.566	0.0196	3	45	60	2	1.237	0.0037
1	16	20	3	-0.628	0.0189	3	46	60	2	0.678	0.0026
1	17	20	3	-0.637	0.0187	3	47	60	2	1.215	0.0146
2	18	30	3	-0.891	0.0056	3	48	60	2	1.936	0.0230
2	19	30	2.5	0.807	0.0164	3	49	60	2	2.007	0.0060
2	20	30	2.5	0.191	0.0111	3	50	60	2	1.944	0.0058
2	21	30	2.5	0.570	0.0141	3	51	60	2	1.891	0.0056
2	22	30	2.5	0.863	0.0169	3	52	60	2	2.402	0.0077
2	23	30	2.5	0.623	0.0146	3	53	60	2	2.493	0.0082
2	24	30	2.5	0.883	0.0172	3	54	60	2	1.529	0.0044
2	25	30	2.5	0.593	0.0143	3	55	60	2	2.437	0.0079
2	26	30	2.5	0.105	0.0105	3	56	60	2	1.807	0.0053
2	27	30	2.5	1.583	0.0268	3	57	60	2	1.698	0.0049
2	28	30	2.5	0.928	0.0177	3	58	60	2	2.444	0.0079
2	29	30	2.5	0.548	0.0139	4	59	100	1.5	2.904	0.0013
2	30	30	2.5	-0.047	0.0095	4	60	100	1.5	2.934	0.0013
Total Probabilities		0.4799 (Zone type 1)		0.4004 (Zone type 2)		0.1171 (Zone type 3)		0.0026 (Zone type 4)			

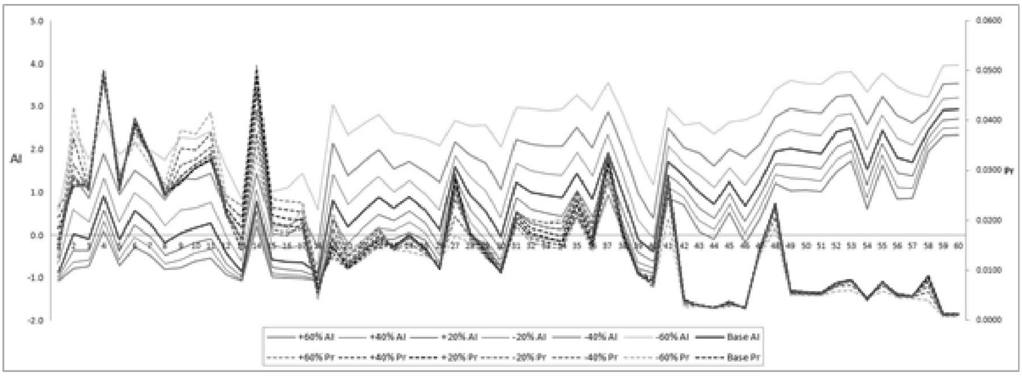
Note: Zone type 1 = Rural zones (1-17), 2 = Suburban zones (18-41), 3 = Urban zones (42-58), 4 = CBD zones (59-60).

Welfare gains and losses (ΔCS) estimated via logsum differences in the base scenario and scenario 2 are quite large: when all GC_{ij} values are increased 20%, 40%, and 60%, the estimated user welfare losses are -\$55,946, -\$98,858, and -\$132,160, as shown in Table 5. When all GC_{ij} values fall 20%, 40%, and 60%, the estimated welfare gains are \$74,127, \$172,506, and \$319,787. As in the case of transit, such results imply that reductions in automobile travel costs impact home buyer welfare more significantly than the same percentage increase in auto travel costs. The above welfare gains and losses are calculated for home buyers with a \$70,000 annual income and 2.4 person household size. For home buyers with \$45,000 annual income and four-person household size, the estimated user welfare changes are -\$36,299, -\$64,083, and -\$85,581 when all GC_{ij} values are increased 20%, 40%, and 60%; they are \$48,151, \$113,699, and \$207,662 when all GC_{ij} values fall by 20%, 40%, and 60%. A \$15-per-hour VOTT was also tested, resulting in higher accessibility indices (than with the \$12-per-hour VOTT used above), but estimated house buyer benefits are smaller than before (i.e., as compared with those shown in Table 5).

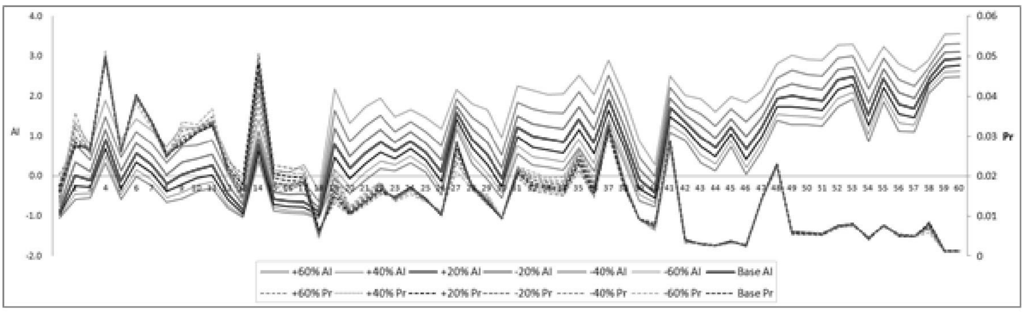
Table 4: Shares of Home Location for Four Types of Zones Following Changes in Variables

		60%	40%	20%	-20%	-40%	-60%
Transit GC	Rural	0.4800	0.4800	0.4800	0.4798	0.4792	0.4754
	Suburban	0.4003	0.4003	0.4003	0.4005	0.4009	0.4039
	Urban	0.1171	0.1171	0.1171	0.1172	0.1173	0.1181
	CBD	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026
Auto GC	Rural	0.5138	0.5009	0.4890	0.4764	0.4824	0.5038
	Suburban	0.3708	0.3807	0.3910	0.4070	0.4081	0.3987
	Urban	0.1125	0.1156	0.1173	0.1142	0.1076	0.0959
	CBD	0.0028	0.0028	0.0027	0.0023	0.0020	0.0016
Auto OC	Rural	0.5030	0.4948	0.4869	0.4744	0.4713	0.4720
	Suburban	0.3804	0.3870	0.3938	0.4064	0.4113	0.4140
	Urban	0.1138	0.1155	0.1167	0.1167	0.1151	0.1119
	CBD	0.0027	0.0027	0.0026	0.0024	0.0023	0.0021
Auto TT	Rural	0.4857	0.4829	0.4810	0.4801	0.4815	0.4844
	Suburban	0.3920	0.3952	0.3980	0.4020	0.4029	0.4029
	Urban	0.1196	0.1192	0.1184	0.1154	0.1132	0.1105
	CBD	0.0028	0.0027	0.0026	0.0025	0.0023	0.0022
Home price	Rural	0.5625	0.5368	0.5094	0.4484	0.4148	0.3791
	Suburban	0.3787	0.3882	0.3956	0.4017	0.3991	0.3918
	Urban	0.0583	0.0740	0.0934	0.1456	0.1792	0.2179
	CBD	0.0005	0.0009	0.0015	0.0042	0.0069	0.0112
Base scenario		Rural: 0.4799; Suburban: 0.4004; Urban: 0.1171; CBD: 0.0026					

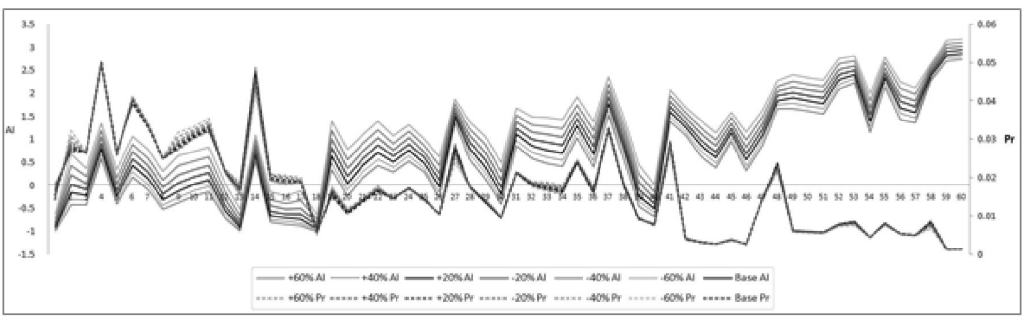
Figure 2: Changes in AI and Zone Choice Probabilities Following Changes in Auto's Total
(Generalized) Costs (a), in Auto's Operating Costs (b), and in Auto's Travel Times (c)



(a)



(b)



(c)

Note: X-axis denotes the 60 zones (potential home locations)

Scenarios 3 and 4 are the detailed analyses of changes in operation cost and travel time inputs of the auto mode. Figures 2(b) and 2(c) describe the AIs and probabilities of each location being chosen under these scenarios. As seen in these figures, line shapes are very similar to those in Figure 2(a), but the spacing between lines is smaller, implying that AI and the probability of a location being chosen are less sensitive to changes in vehicle operation costs and travel times than to changes in overall generalized costs. In Scenario 3, for example, when all operation cost values are increased 40%, the total probabilities of location choices in rural and CBD zones rise by 0.0149 and 0.0001(from Table 4: 0.4948-0.4799 = 0.0149 and 0.0027-0.0026 = 0.0001), on average, while those in suburban and urban zones drop an average of 0.0134 and 0.0016 (from Table 4: 0.4004-0.387 = 0.0134 and 0.1171-0.1155 = 0.0016); when all operation cost values fall by 40%, the total probability of choosing a suburban zone rises by 0.0109 (from Table 4: 0.4113-0.4004 = 0.0109), while choice probabilities of each rural, urban, and CBD zones drop an average of 0.0086, 0.0020, and 0.0003 (from Table 4: 0.4799-0.4713 = 0.0086, 0.1171-0.1151 = 0.0020 and 0.0026-0.0023 = 0.0003). As discussed previously, AIs of rural and suburban zones are more sensitive to the road networks changes. Scenario 4 offers almost the same trend as shown in Scenario 3. In comparing results of Scenarios 3 and 4, one can see how lower vehicle operations costs may provide more benefits to new home buyers than reduced travel time when they are changed by the same proportion or percentage. For example, the estimated average welfare effect is $99,940 when all operating costs fall 40%, versus $51,546 when all travel times fall 40%. Table 5 shows these numbers in detail.

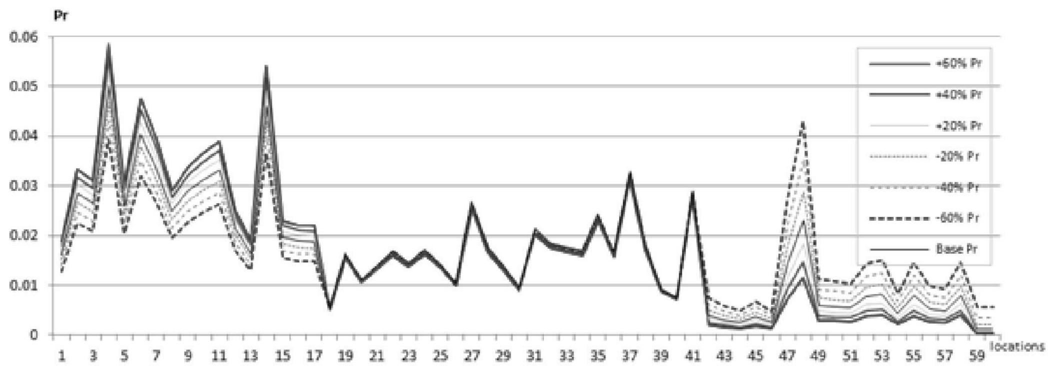
Scenario 5 explores the effect of home price on people's home location choices and welfare. As displayed in Figure 3, the shares of location choice in suburban zones are less sensitive to home price shifts (as compared with all other zone types). For example, zones 10, 37, 48, and 60 exist in rural, suburban, urban, and CBD locations, respectively. When all home price values increase 40%, the shares of these four representative zones shift by 0.0037, -0.0010, -0.0085, and -0.0008, respectively, compared with their original probabilities, shown in Table 3: 0.0312, 0.0328, 0.0230, and 0.0013). The corresponding estimated welfare losses are -$56,678, -$111,383, and -$164,438 when all home prices increase 20%, 40%, and 60%, and welfare gains are $59,036, $120,885, and $186,079 when home price fall 20%, 40%, and 60. When one changes VOTT from $12 to $15 per hour, the benefits one observes following house price reductions (in Table 5, with superscripts) are smaller than before, while losses from house price increases are somewhat greater than before. It seems home buyer benefits are impacted slightly more when home prices fall than when they rise by the same amount (in dollars or percentage terms).

Table 5: Welfare Effects of Changing Travel Costs, Times, and Home Prices
(Income = $70,000, Household size = 2.4 persons, VOTT = $12/hr)

Changes Scenarios	+60%	+40%	+20%	-20%	-40%	-60%
Transit GC	-$47.7	-$42.6	-$30.8	$101.1	$591.5	$4,870
Auto GC	-$132,160	-$98,858	-$55,946	$74,127	$172,506	$319,787
Auto OC	-$94,290	-$68,089	-$37,063	$44,808	$99,940	$169,692
Auto TT	-$61,040	-$42,585	-$22,303	$24,537	$51,546	$81,299
Home Price	-$164,438	-$111,383	-$56,678	$59,036	$120,885	$186,079
Auto GC[1]	-$80,661	-$60847	-$34,755	$46,993	$112,094	$206,804
Home Price[1]	-$174,640	-$124,185	-$72,106	$38,989	$99,511	$176,764

[1] These results presume VOTT = $15/hr

Figure 3: Changes in Zone Choice Probabilities Following Home-Price Changes



Note: X-axis denotes the 60 zones (potential home locations).

CONCLUSIONS

An understanding of residential location choice provides a foundation to explore the relationship between land use and transportation, which leads to more accurate travel demand models. Previous research on household location choice usually focuses on the factors affecting the household buyer's location choice decision, with accessibility generally accepted as a principal determinant of residential location selection. In this paper, a three-layer NL structure on house location choice is proposed and logsum differences are used to estimate home buyers' welfare changes as a result of various transportation and housing input changes. The systematic utility of a residence is considered as a function of home price, home size, and home location zone's accessibility. This paper develops several scenarios to examine how transportation and housing price factors affect house location choice behavior and household welfare, with an emphasis on new buyers (rather than existing owners, who are also affected by personal-wealth changes, when the values of their existing properties shift, following AI changes).

Home buyer (or residential locator) welfare estimated via logsum differences are estimated to be very small due to changes in the generalized cost of transit; and location choice probabilities remain very stable when raising or lowering all transit travel time and/or cost values. In most U.S. settings and many other regions of the world, access costs via automobile are very important for home location choice. Decreasing travel costs and/or travel times have a more significant impact on home buyer welfare than increasing them; and the higher the AIs, the larger the buyers' choice probabilities in most rural and suburban areas. It is also implied that in urban and CBD areas, home buyers usually pay more attention to home price or home size. The relative significance of home price changes on home-buyer welfare is apparent, as compared with similar (scaled) shifts in the values of other attributes: new locators benefit more when home prices fall by the same amount, both in dollar terms and percentage terms.

These findings are meaningful for many stakeholders when anticipating the economic impacts of evolving transportation systems in the face of new investments, rising travel demands, distance-based tolls, self-driving vehicles, and other changes. Land values and home prices are a major economic policy concern for growing and popular regions, as rents rise and welfare can fall, even if transportation systems are being improved. The London region, San Francisco Bay Area, Auckland, and even Austin, Texas, face serious social and economic issues relating to housing and transport. This paper provides a method for and realistic examples of a holistic view that educates planners, economics, engineers, and policymakers.

Of course, the analysis pursued here illustrates only a limited number of idealized scenarios under a nested logit model structure, and focuses on home buyers rather than renters. Many other investigative opportunities and scenario extensions are feasible, which may highlight other key factors for regional welfare analysis following changes in the transportation and/or land use systems. For example, one could examine the effects of changes in zone attractiveness, model parameters, and various other inputs, simultaneously or independently. One could use Bina et al.'s (2006) parameters for renters' location choices and parameters for rent variations across locations and dwelling types to anticipate welfare impacts on this other very important class of locators. User heterogeneity is also important to explore in more depth, since every household differs (in its demographic attributes, income, housing preference function, and values of travel time, for example). Moreover, uncertainty exists in all zones (and for all model parameters, as well as the model specification itself), with spatial autocorrelation in missing variables; and there are significant information-limitation issues for many movers (especially those new to a region) when evaluating a region's many location options. Thus, this topic area remains ripe for future investigation.

A variety of other, and ideally more realistic, changes to the transportation system would be very useful to explore here to further describe the changes in AIs, choices, and welfare levels. The possibilities are limitless, and the big changes simulated here, across the zone system, may provide upper bounds on the magnitudes of experience one might expect, which can be useful for evaluating shocks like major recessions (when travel demands fall substantially) or expansionary periods, and changes in transport technology (e.g., self-driving cars lowering perceived travel costs dramatically). The future is always uncertain, but it is wise to anticipate land price and welfare effects well in advance to shape policies and practices that enhance local and regional communities.

Acknowledgements

The authors greatly appreciate Donna Chen's and anonymous reviewers' careful review of this paper, the administrative contributions of Ms. Annette Perrone and Scott Schauer-West, and the financial support of the China Scholarship Council, which funded the lead author's one-year stay in the U.S.

Endnotes

1. Logsums are the natural log of summations of exponential functions of the systematic utilities across alternatives, under a logit-choice-model specification. Logsum differences quantify changes in expected maximum utilities and thus consumer surplus before and after the change.

2. Bina and Kockelman (2006, 2009) explored the mean rank of importance of housing and location attributes from two mover segments: home buyers and apartment renters. They found that home price (or apartment rent), travel time (to work), and access to major freeways are the most important attributes for home buyers and apartment buyers - among almost 20 attributes. Home size (including number of bedrooms and lot size) is also top-ranked by most home buyers.

3. The rule-of-half method (RoH) is a traditional method for calculating consumer surplus in transport economics. It assumes that the consumer demand curve is linear with respect to generalized costs, at least between original and new demand values. When generalized cost changes from GC^0 to GC^1, travel demand (in the form of person-trips) will change from T^0 to T^1. The change in consumer surplus (ΔCS) can be computed as follows:
   $$\Delta CS = \frac{1}{2}(T^1 + T^0)(GC^0 \quad GC^1) .$$

4. Zhou and Kockelman (2011) proposed a dwelling unit and location choice model for Austin's households based on a survey of Austin movers in 2005, and estimated coefficients on home price-to-income ratio and SF (square feet)-per-household-member variables to be -0.249 and +3.34. According to "City of Austin Community Inventory Report," from 2000 to 2007, the average median household annual income is between \$60,000 to \$70,000, household size is between 2.2 to 2.4 (and shows a declining trend). Thus, in this paper, an average household income \$70,000 and an average household size 2.4 are assumed (usually, the new home buyer households are wealthier and bigger-size than average households in Austin. In Bina and Kockelman (2009), the surveyed new home buyer's average income was \$93,256, and average household size was 2.27. Here, with the home price (P) and SF instead of home price-to-income ratio and SF-per-household-member, the values of α_1 and α_2 can be estimated as $\alpha_1 = -0.249/7 = -0.0357$ and $\alpha_2 = 3.34/2.4 = 1.39$.

5. Kockelman and Lemp (2011) relied on a four-layer (destination, mode, time of day, and route) NL model, with scale parameters (μ_1, μ_2, μ_3, μ_4,) from the lowest-level nest to the highest-level nest assumed to be 1.8, 1.6, 1.4, and 1.2, to be consistent with random utility maximization theory (Ben-Akiva and Lerman 1985).

6. Skim files are optimal/shortest travel times and costs between all origin-destination pairs, by mode, following a loading of demand onto the network, and solving for a user equilibrium, where no one can improve his/her generalized cost of travel.

7. According to AAA (2013), the average cost of driving a medium sedan 15,000 miles a year was \$0.61 per mile in 2013. Here, a value of \$0.60 per mile is used to estimate the $COST_{ldm}$ value shown in Equation 4.

References

AAA "Your Driving Costs: How Much Are You Really Paying to Drive?" AAA Association Communication, Heathrow, FL, 2013. Available at http://newsroom.aaa.com/wp-content/uploads/2013/04/YourDrivingCosts2013.pdf.

Allen, G. "Highway Noise, Noise Mitigation, and Residential Property Values." *Transportation Research Record* 812, (1981): 21-27.

Alonso, W. *Location and Land Use: Toward a General Theory of Land Rent*. Harvard University Press, Cambridge, MA, 1964.

Bajic, V. "The Effects of a New Subway Line on Housing Prices in Metropolitan Toronto." *Urban Studies* 20, (1983): 149-158.

Ben-Akiva, M., and S. Lerman. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, 1985.

Ben-Akiva, M., and J.L. Bowman: "Integration of an Activity-based Model System and a Residential Location Model." *Urban Studies* 35, (1998): 1131-1153.

Bina, M., and K.M. Kockelman. "Location Choice vis-à-vis Transportation: The Case of Recent Homebuyers." *The Expanding Sphere of Travel Behaviour Research* 18, (2009): 597-619.

Bina, M., V. Warburg, and K.M. Kockelman "Location Choice vis-à-vis Transportation: The Case of Apartment Dwellers." *Transportation Research Record* (2006): 93-102.

Castiglione, J. J., Freedman and W. Davidson. "Application of a Tour-based Microsimulation Model to a Major Transit Investment." San Francisco County Transportation Authority and PB Consult, San Francisco, California, 2003.

Dang, Y., W. Zhang, and W. Wu. "Residents Housing Preferences and Consuming Behaviors in a Transitional Economy: New Evidence from Beijing, China." *Progress in Geography* 30(10), (2011):1203-1209.

EXPEDITE Consortium. *EXPEDITE Final Publishable Report*. Report for European Commission, DGTREN, RAND Europe, Leiden, 2002.

FHWA. *Work Zone Road User Costs - Concepts and Applications*. US Department of Transportation, Federal Highway Administration. Available at http://ops.fhwa.dot.gov/wz/resources/publications/fhwahop12005/sec2.htm (2015).

Geurs, K., B. Zondag, G. de Jong de, and M. de Bok. "Accessibility Appraisal of Land-Use / Transport Policy Strategies: More Than Just Adding up Travel-Time Savings." *Transportation Research* Part D, (2010): 382-393.

Habib, K.M., and K.M. Kockelman, "Modeling the Choice of Residential Location and Home Type: Recent Movers in Austin, Texas." Proceedings of the 87th Annual Meeting of the Transportation Research Board, (2008).

Hollingworth, B.J., and E.J. Miller. "Retrospective Interviews and its Application in Study of Residential Mobility." *Transportation Research Record* 1551, (1996): 74-81.

Hunt J.D., J.D.P. McMillan, and J.E. Abraham. "Stated Preference Investigation of Influences on Attractiveness of Residential Locations." *Transportation Research Record* 1466, (1994): 79–87.

Jong, G. de, M., A. Pieters , I. Daly, E. Graafland, Kroes, and C. Koopmans. "Using the Logsum as an Evaluation Measure: Literature and Case Study." Prepared for AVV Transport Research Centre. RAND Europe, 2005.

Kalmanje, S., and K.M. Kockelman, "Credit-Based Congestion Pricing: Travel, Land Value and Welfare Impacts," *Transportation Research Record* 1864, (2004): 45-53.

Kockelman, K.M., and J.D. Lemp "Anticipating New-Highway Impacts: Opportunities for Welfare Analysis and Credit-Based Congestion Pricing. *Transportation Research* Part A 45 (8), (2011): 825-838.

Lee, B.H.Y, P. Waddell, L. Wang, and R.M. Pendyala. "Reexamining the Influence of Work and Nonwork Accessibility on Residential Location Choices with a Micro Analytic Framework." *Environment and Planning A* 42, (2010): 913-930.

Lee, B.H.Y., and P. Waddell "Residential Mobility and Location Choice: A Nested Logit Model with Sampling of Alternatives." *Transportation* 37(4), (2010): 587-601.

McFadden, D. "Modeling the Choice of Residential Location." A. Karlqvist, L. Lundqvist, F. Snickars, and J. Weibull, (eds). *Spatial Interaction Theory and Residential Location*. Amsterdam, North-Holland, Amsterdam, (1978).

McFadden, D. “Econometric Models of Probabilistic Choice.” C. Manski, and D. McFadden, (eds). *Structural Analysis of Discrete Data: With Econometric Applications*. Cambridge, Massachusetts, MIT Press (1981).

Mohring, H. “Land Values and the Measurement of Highway Benefits.” *Journal of Political Economy* 49, (1961): 236-249.

Nelson, J.P. “Highway Noise and Property Values: A Survey of Recent Evidence.” *Journal of Transport Economics and Policy* 16(2), (1982): 117-38.

Odeck, J., J. Rekdal, and T.N. Hamre “The Socio-Economic Benefits of Moving from Cordon Toll to Congestion Pricing: The Case of Oslo.” Proceedings of the 82th Annual Meeting of the Transportation Research Board, Washington D.C., (2003).

Ommeren, J.V., P. Roedveld, and P. Nijkamp. “Job Moving, Residential Moving and Commuting: A Search Perspective.” *Journal of Urban Economics* 46, (1999): 230-253.

Pinto, S.M. “Residential Choice, Mobility and the Labour Market.” *Journal of Urban Economics* 51, (2002): 469-496.

Rossi, P. *Why Families Move*. McMillan, New York, 1955.

Sermons, M.W., and F.S. Koppelman. “Representing the Differences Between Female and Male Commute Behavior in Residential Location Choice Models.” *Journal of Transport Geography* 9 (2), (2001): 101–110.

Srour, I.M., K.M. Kockelman, and T.P. Dunn. “Accessibility Indices Connection to Residential Land Prices and Location Choices.” *Transportation Research Record* 1805, (2002): 25-34.

Ten Siethoff, B., and K. Kockelman, “Property Values and Highway Expansions: An Investigation of Timing, Size, Location, and Use Effects.” *Transportation Research Record* 1812, (2002): 191-20.

Tu, Y., and J. Goldfinch “A Two-Stage Housing Choice Forecasting Model.” *Urban Studies* 33 (3), (1996): 517–537.

US Department of Transportation, Federal Highway Administration Case Study: Sacramento, California. *Methodology Calculation of User Benefits*, USDOT, (2004).

Voith, R. “Transportation, Sorting, and Housing Values.” *AREUEA Journal* 19 (2), (1991): 117-137.

Yang, J. “Transportation Implications of Land Development in a Transitional Economy: Evidence from Housing Relocation in Beijing.” *Transportation Research Record* 1954, (2006): 7-14.

Zhang, W., and K.M. Kockelman. “Modeling Cities with Congestion and Agglomeration Externalities: The Efficiency of Congestion Tolls, Labor Subsidies, and Urban Growth Boundaries.” Under final review for publication in *Journal of Urban Economics*, (2015). http://www.ce.utexas.edu/prof/kockelman/public_html/trb14ugbsvstollingrents.pdf

Zhou, B., and K.M. Kockelman. “Microsimulation of Residential Land Development and Household Location Choices: Bidding for Land in Austin, Texas.” *Transportation Research Record* 2077, (2008a): 106-112.

Zhou, B., and K.M. Kockelman. "Self-Selection in Home Choice: Use of Treatment Effects in Evaluating the Relationship Between the Built Environment and Travel Behavior." *Transportation Research Record* 2077, (2008b): 54–61.

Zhou, B., and K.M. Kockelman. "Neighborhood Impacts on Land Use Change: a Multinomial Logit Model of Spatial Relationships." *Annals of Regional Science* 42(2), (2008c): 321-340.

Zhou, B., and K.M. Kockelman. "Land Use Change Through Microsimulation of Market Dynamics: An Agent-based Model of Land Development and Locator Bidding." *Transportation Research Record* 2255, (2011): 125-136.

Zondag, B., and M. Pieters. "Influence of Accessibility on Residential Location Choice." *Transportation Research Record* 1902, (2006): 63-70.

Shuhong Ma *is an associate professor in the Traffic Engineering Department School of Highways at Chang'an University. Ma's main research interests are transportation planning and policy-making, system evaluation, and traveler behavior in response to pricing and policy. She has been, and continues to be, involved in many projects in this area and has published extensively in this area of research. Ma's current research focuses on the relationship between accessibility and public transit system in Xi'an City. Prior to teaching and researching at Chang'an University, she obtained her BS in 1999 and master's in 2002 in transportation engineering from Chang'an University. In 2008, she received her doctoral degree.*

Kara Kockelman *is a registered professional engineer and holds a PhD, 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 is primary and co-author of over 140 journal articles (and one book) across a variety of subjects, nearly all of which involve transportation-related data analysis. Her primary research interests include planning for shared and autonomous vehicle systems, 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.*

The Multimodal Connectivity at Bus Rapid Transit (BRT) Stations and the Impact on Ridership

by Mintesnot Woldeamanuel and Craig Olwert

A multimodality index (MI) is developed to evaluate the accessibility and convenience of transit use by investigating the connectivity of a Bus Rapid Transit (BRT) with other modes of travel. Better connected stations increase transit system ridership, resulting in environmental and social equity gains. The integration of the Orange Line BRT system in Los Angeles with other travel modes, including bicycles, pedestrians, regular buses, and private automobiles, was analyzed using field observations and LA Metro data to create a multimodality index (MI). While multimodal connectivity of the Orange Line BRT system varies across stations, a positive relationship exists between ridership and the MI, indicating that the MI is a reliable predictor of transit ridership and a useful tool for transit planning.

INTRODUCTION

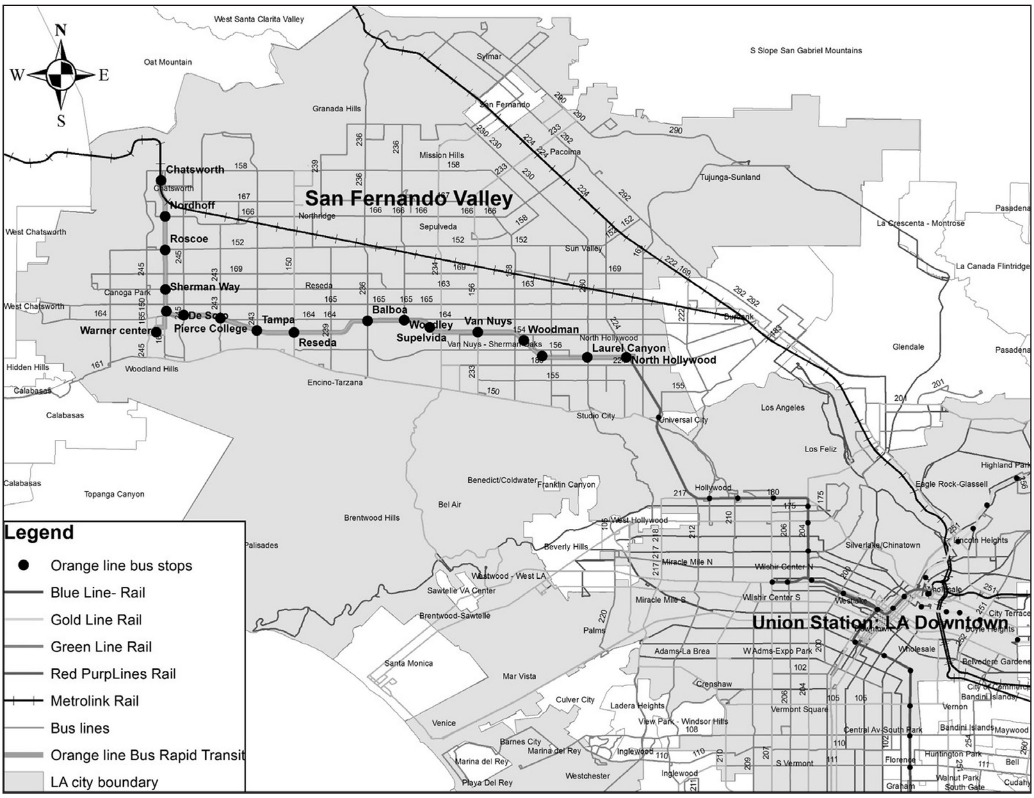
Urban residents frequently utilize multiple transportation modes to travel across the city, making their trips multimodal (Keshkamat et al. 2009; Liu 2011). Multimodal transportation is the use of two or more modes to move people or goods from an origin to a destination (DeWitt and Clinger 2000); and a multimodal transportation system is a system that elegantly integrates multiple travel modes across an urbanized area (Bielli et al. 2006). Public transit, especially Bus Rapid Transit (BRT), is an important part of a multimodal system. Dill et al. (2013) found that BRT ridership depends on several station-level factors, including multimodal connectivity. BRT is considered an ideal form of public transportation because its flexibility, affordability, and accessibility provide overall positive environmental and social benefits (Cain et al. 2007; Hidalgo and Carrigan 2010; Vincent and Jerram 2006; Wright and Fulton 2005; Cervero 2013). So, increasing multimodal connectivity to BRT increases accessibility and reduces traffic congestion, roadway costs, and energy consumption.

Rickert (2010), Duarte and Rojas (2012), and Dill et al. (2013) found that the connectivity of a BRT with walking, cycling, automobile, and other forms of public transit increases ridership. Higher ridership occurs because patrons know they have a convenient alternative transportation mode to complete their first and last miles of their overall trip. When stations and areas surrounding the stations are designed to integrate alternative travel modes, BRT ridership increases and multimodal patrons have more efficient trips. In 2014, the Institute for Transportation and Development Policy's (ITDP) BRT Standard (2014) identified only four qualified BRT systems: Cleveland, Ohio; Los Angeles Metro Orange Line; Eugene, Oregon; and San Bernardino, California (operational as of April 2014 and not assessed yet). This study will determine the Los Angeles Metro Orange Line station's multimodal connectivity and the effects on ridership.

The Metro Orange Line serves passengers in Los Angeles' suburban San Fernando Valley. Orange Line users can access stations by transferring from commuter rail, subway, and regular bus; biking; walking; driving individual automobiles using park-n-ride facilities, and carpooling and taxis using *kiss-n-ride* (drop off locations where cars can drop off and pick up passengers). The terminus stations have access to larger mass transit systems. At the North Hollywood station, the Orange Line connects to the Red Line subway, which travels through famous population and employment centers including Hollywood, Koreatown, and Downtown Los Angeles. The Orange Line's northwest terminus, the Chatsworth Station, connects passengers to Metrolink (regional) and Amtrak (national) rail service. The Orange Line provides a practical alternative to the automobile, the main mode of transportation in the San Fernando Valley for work, school, shopping, and entertainment trips. The Orange Line began service in October 2005 and was extended from Warner Center to Chatsworth in June 2012. It has quickly exceeded the initial planned ridership levels. Exploring the Orange Line's ridership and multimodal connectivity will allow transit planners to better understand how to make successful BRT systems.

Thus, the infrastructure at and around the Orange Line stations will be analyzed to determine if multimodal connectivity impacts ridership. Pedestrian, cyclist, transit, car, and taxi connections will be examined at each station to determine if ridership is higher at stations with better multimodal connectivity.

Figure 1: The BRT Orange Line in San Fernando Valley



LITERATURE REVIEW

Since World War II, transportation planning in the United States focused on maximizing the efficiency and speed of one mode of transportation (usually the automobile) rather than evaluating and increasing the efficiency of a user's multimodal trip. Building highways was the main priority of transportation legislation until the passage of the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) shifted the focus to multimodal trips (Dilger 1992). In this new era, comprehensive assessments of different travel modes' connectivity were used by metropolitan agencies to develop sustainable transportation systems and to influence local and regional transportation and land use plans (Strate et al. 1997).

Since ISTEA, transportation planning research and transportation modeling techniques account for a wider range of travel options, including walking, biking, carpool, and public transit and evaluate the multimodal system's effect on emissions and land use. This new paradigm recognizes that the ultimate goal is accessibility: people's overall ability to quickly reach desired services and activities

(Litman 2014). Thus, a multimodal transportation system increases the options provided for users to best meet their needs and preferences (Mahrous 2012; Talbott 2011; Cervero and Kockelman 1997; Polat 2012; Nobis 2006; Godefrooij et al. 2009).

While research has focused on the multimodal network at a system level (Bielli et al. 2006; Hochmair 2008), multimodal access at stations has also been studied (Kerman et. al, 2014; Iseki et al. 2007). Kerman et al. (2014) found that transit station design can increase connectivity for pedestrians, bikers, and transit and automobile users. Increased connectivity, with more direct walking routes and better pedestrian facilities, increases the likelihood of transit being incorporated into a multimodal trip (Dill 2004; Moudon et al. 1997; Frank et al. 2005). Dill (2004) identified sidewalk coverage, average block size, and intersection density as three indicators of connectivity. The recommended target for sidewalk coverage, the percent of streets with sidewalks on both sides of the streets within one-half-mile of a station, is 67%. Smaller block sizes increase the station permeability by increasing pedestrian route choices to access transit, with a recommended size of four acres or less. Higher intersection density, the number of four-way intersections per acre, increases the likelihood for more walking routes and increases the ability of a user to take the most direct route (Dill 2004).

Public transit and bicycles are highly compatible modes of transportation (Nelson and Nygaard 2009), so facilitating bicycle access to transit facilities can increase transit ridership. Providing direct, safe routes to stations with dedicated bike lanes and allowing bikes aboard BRT vehicles increases ridership, particularly for routes that carry many riders who travel long distances and collect riders from lower density neighborhoods. Nelson and Nygaard (2009) argue that bike storage at stations and accommodating bicycles aboard BRT vehicles promotes multimodal corridor ridership. Olwert et al. (2015) found that when the Metro Orange Line evening service was increased, stranded cyclists decreased and bicycle ridership increased.

Besides walking and bicycling, other multimodal users arrive by transit and automobile. Evans (2004) found when wait times for BRT customers transferring from local feeder service exceeded 7.5 minutes, ridership decreased. However, when timing of the transfers was optimized and walking connections were minimized, BRT ridership increased (Evans 2004). BRT ridership also increases when more park-n-ride spaces are added. Levinson and Weant (2000) found that ridership increases by 0.74 to 0.77 riders per added parking space with 0.11 to 0.60 of them being new riders.

Multimodal accessibility has been evaluated in several ways: evaluating the immediate area to a transit station, considering the overall transportation system connectivity, and finally, looking at station specific attributes. By looking at the area immediate to a station, researchers have found ways to make recommendations to increase multimodal accessibility at the stations by improvements in an area surrounding the station. Iseki et al. (2007) developed an evaluation tool to assess the quality of transit transfer facilities by focusing on items that improve a passenger's experience: minimal transfer time and distances, and maximum convenience, comfort, safety, and security. Guttenplan and Reynolds (2012) analyzed the level of service (LOS) for connecting modes (automobile, transit, bicycle, and pedestrian) based on the urban street design and operations around the transit stations. The resulting report card evaluates how well streets meet the needs of its different users.

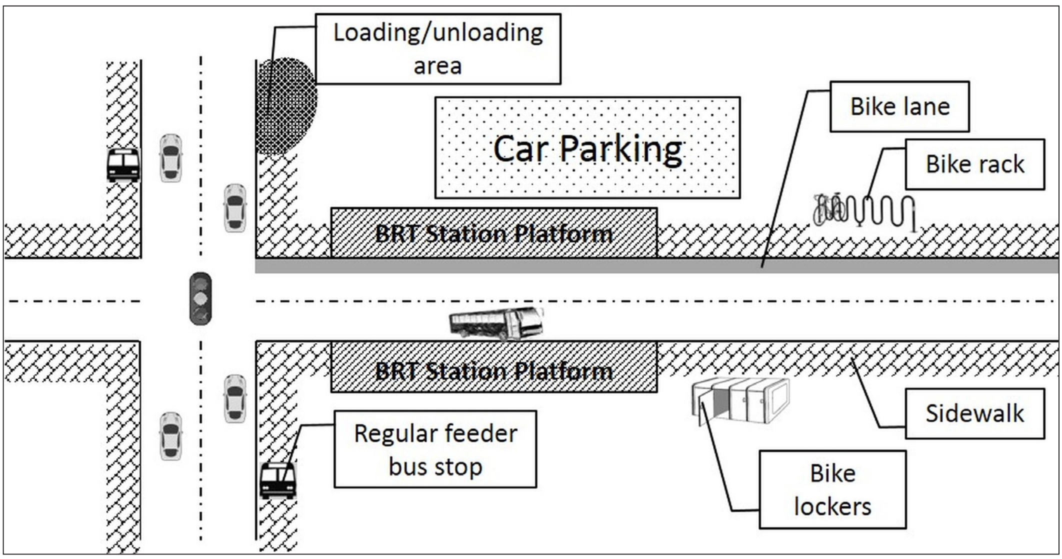
Frank (2008) applied the traditional shortest path algorithms to create integration between different travel modes across the transportation system. Scheurer and Curtis (2008) used spatial network analysis of a multimodal urban transport systems tool (SNAMUTS) to identify and visualize strengths and weaknesses of geographical coverage, network connectivity, competitive speed and service levels to understand the multimodal connectivity of a transportation system. Waddell and Nourzad (2002) used regional accessibility of a neighborhood to assess the multimodal connectivity of the overall transportation system.

Although a system level multimodality analysis is the focus of the above-mentioned studies, some research focuses on station-level connectivity analysis. Martens (2007) analyzed the impact of bicycle infrastructure at stations on ridership and the results indicate that improved bicycle services at stations lead to an increase in public transport ridership and a (small) decrease in car use on specific routes. Duarte and Rojas (2012) evaluated Curitiba and Bogota's BRT stations to determine if different modes of transportation were connected, including sidewalk access, bicycle parking, car parking, and accessibility for the disabled. They found that Bogota's BRT stations had better pedestrian and bicycle access than Curitiba. Neither of the cities had good access for private cars but better access for taxis. Our study further extends the literature on station level connectivity and their influence on ridership.

DATA AND METHODS

The goal of this study is to create a multimodality index (MI) that comprehensively measures a BRT station's connectivity. Station elements that facilitate access by multiple modes were incorporated, including availability and quality of nearby sidewalks, availability of bike infrastructure, availability of parking for cars and bikes, connectivity to regular feeder buses, and presence of kiss-n-ride facilities. Field observations were made within a 100-feet radius for all 18 BRT Orange Line stations using a standardized checklist for all five variable categories included in the MI calculation.

Figure 2: Multimodal Features for Ideal Connectivity



Data for Multimodality Index

Trained field observers assessed the following features: sidewalks, bikeways, parking, bus connections, and taxi and/or kiss-n-ride. This section explains the grading systems and how data for the index calculation were derived.

1. **Sidewalks.** All streets segments within a 100-feet radius of the platform's peripheral point were assigned a grade of 1-5 based on sidewalk availability, quality and compliance with the Americans with Disabilities Act (ADA). A detailed description of the sidewalk grading system is presented in Table 1. The final sidewalk assessment score for each station was calculated as the average sidewalk quality score of all street segments in the station buffer area (an area that covers a 100-foot radius around the platform's peripheral point).

Table 1: Sidewalk Quality Scale

Grade	Description	Picture representation
1	**EXTREMELY POOR QUALITY SIDEWALK:** Unpaved path, sloping, uneven dirt or grass. A score of 1 means that no sidewalk is present: no pavement	
2	**POOR QUALITY SIDEWALK:** Discontinuous paved sidewalk. A grade 2 sidewalk is non-continuous. There are stretches of pavement, but also sections of grass and/or dirt. In Los Angeles, some properties have a paved sidewalk in front of them and others have dirt or grass. Sidewalks of grade 2 are hazardous because they may seem walkable but can easily cause a person to fall because of the varied surfaces.	
3	**FAIR QUALITY SIDEWALK:** Paved sidewalk, with many obstacles: large cracks or bumps that can cause a person to trip or fall. Injuries can occur from falls on the cracks and bumps, especially for children and the elderly.	
4	**VERY GOOD QUALITY SIDEWALK:** Paved level sidewalk with no surface obstacles, *without* ADA-complaint ramps at crossings.	
5	**EXTREMELY GOOD QUALITY SIDEWALK:** Paved level sidewalk with no surface obstacles, *with* ADA compliant ramps at crossings.	

Source of pictures: ©2015 Google Map

2. **Bikeways.** The length of Class I, II, and III bicycle infrastructure within a 100-feet radius of the stations was used to create a bike quality score. The Los Angeles Metropolitan Transportation Authority defines the three classes of bicycle right-of-ways as shown in Table 2. Utilizing field observation, all streets and right-of-ways within the station buffer was classified. GIS was then used to calculate the length of each bicycle right-of-way classification for each BRT station. The data were inputted into the Bikeway Quality equation, presented below, which expresses each station bike score as a ratio weighted by the access quality of each classification.

$$(1)\quad Bikeway\ Quality\ Score = \frac{3l_1 + 2l_2 + l_3}{\sum_{i=1}^{3} l_i}$$

where, l is the length of the road segments of each of the three class types i.

3. **Parking**. Counts of available parking spaces were recorded as continuous variables in three mode categories: 1) car parking spaces, 2) bike lockers, and 3) bike racks
4. **Bus Connections**. Using the Los Angeles Metropolitan Transportation Authority transit line maps, the count of regular, express, and municipal bus connections to each Orange Line BRT station was recorded as continuous variable data. Connections were defined as the number of other transit lines which intersect and stop at an Orange Line BRT station.
5. **Taxi and/or Kiss-n-ride**. The presence of designated taxi and passenger kiss-n-ride zones was recorded as a binary variable (available=1; not available=0). Designated facilities, marked by signage, could be provided as short-term parking spaces, turnout areas, and curbside temporary parking.

Table 2: Classification for Bikeways

Class	Description	Picture representation
Class I	A class I bicycle path is completely separated from automobile traffic. Class I paths are usually found along current transit systems, rivers, parks, and/or former train track corridors.	
Class II	A class II bicycle lane is on-street with painted striping to separate cyclists from moving traffic and parked cars. This is the most common class in Los Angeles.	
Class III	A bike route or a sharrow is not a lane or a path. Markings or signage remind automobile drivers that cyclists may be present.	

Source of pictures: ©2015 Google Map

Table 3: BRT Station Amenities Used to Calculate the MI

Stations	Sidewalk quality (out of 5)	Bikeway quality score	Bike rack spaces (count)	Bike locker spaces (count)	Car parking spaces (count)	Kiss-n-ride facility available	Public transit connections (count)	Area characteristics	Multimodality Index (MI)	Total boarding (2014)
Chatsworth	4	2.5	16	16	610	1	9	Terminus	8.14	16,391
Nordhoff	3.38	2.5	12	8	0	0	2	Industrial/ Employment center	-2.77	10,145
Roscoe	4	2.5	12	8	0	0	2	Residential	-0.50	22,437
Sherman Way	3.98	2.5	12	16	207	1	2	Residential	1.91	29,201
Warner Center	4.5	2	6	0	0	0	11	Employment center	3.31	20,937
Canoga	4	1.5	24	32	288	1	2	Employment center/retail	5.29	33,571
De Soto	2.88	1.2	12	8	0	0	4	College	-5.65	14,807
Pierce College	3.25	1.5	12	8	373	1	2	College	-2.98	24,948
Tampa	3.25	1.5	12	8	0	1	1	Residential	-4.55	12,840
Reseda	3.63	2.5	6	16	522	1	2	Residential/retail	0.01	53,463
Balboa	4	2.75	12	20	270	1	5	Residential	4.83	27,121
Woodley	3.17	2.75	8	16	0	0	2	Residential	-3.11	17,876
Sepulveda	4.33	1.5	12	12	1205	1	2	Residential/retail	3.62	37,964
Van Nuys	3.75	2.5	12	8	776	1	8	Employment center/retail	5.16	81,260
Woodman	2.5	2.5	12	8	0	0	3	Residential	-5.35	20,513
Valley College	2.88	2.5	8	8	0	0	5	College	-3.76	21,734
Laurel Canyon	4	2	8	8	0	0	3	Residential	-1.76	29,241
North Hollywood	4	1	8	32	952	1	12	Terminus	8.15	167,514
Mean	*3.64*	*2.09*	*11.33*	*12.89*	*289.06*	*0.56*	*4.28*		0.56	35,664.61
SD	*0.55*	*0.57*	*4.12*	*8.41*	*378.77*	*0.51*	*3.41*		4.59	36,918.99
Min.	*2.5*	*1*	*6*	*0*	*0*	*0*	*1*		-5.65	10,145
Max.	*4.5*	*2.75*	*24*	*32*	*1205*	*1*	*12*		8.15	167,514

Data for Statistical Analysis

Station-level boarding and socio-economic data were collected for each station. Ridership data for the BRT Orange Line wer obtained from the Los Angeles Metropolitan Transportation Authority for the year 2014. Socio-economic data were obtained from several open source databases: the American Community Survey, Zillow, and Great Schools (a non-profit organization which provides nationwide school statistics). The following control variables were obtained for a one-mile radius from each station: density (measured in persons/acre), the distance from downtown (Union Station), the log of household income for the census tracts adjacent to the station, and the number of high schools within a mile radius from the station. The control variables are chosen with the assumption that denser areas have more people closer to stations that can use transit (Kolko 2011); stations closer to downtown are likely to have more ridership due to proximity to residences, shopping, and jobs; richer households are more likely to operate their own personal vehicles and not use transit (Neff 2007); and a larger number of teenagers in the area are expected to increase a population of more mobile residents who are less likely to have their own personal vehicles (Woldeamanuel 2014). The 2014 boarding data were available for both east and west travel, so west boarding was added as a dummy control variable. The data were also available by month (except for incomplete November data that were removed) so March, which had the highest ridership, was used as the reference variable and dummy variables were added for the rest of the months. Metro also collect the data as weekday, Saturday, and Sunday boarding. Because of commuting, higher numbers are expected during the weekdays, so Saturday and Sunday were both added as dummy variables because of expected lower ridership during the weekend.

Table 4: Data for Statistical Analysis

Variables	Mean	Std. Dev.	Min.	Max.
Station Boarding				
Total boarding (2014) per station	35,664.61	36,918.99	10,145	167,514
Westbound boarding (2014) per station	17,601.83	37,972.49	0	167,514
Eastbound boarding (2014) per station	18,062.78	12,047.38	0	54,663
Weekdays boarding (2014) per station	17,402.06	16,888.02	5,618	77,303
Saturday boarding (2014) per station	10,334.44	11,239.88	2,601	50,411
Sunday boarding (2014) per station	7,928.11	8,951.76	1,926	39,800
Control Variables (1-mile radius)				
High Schools (count)	3.44	2.04	0	7
Median Household Income ($)	53,658	9,784	41,910	73,557
Population Density (persons/acre)	16.66	6.31	6.58	26.14
Distance from Union Station (miles)	21.95	6.37	12.7	33

Multimodality Index Calculation

The multimodality index represents the relative ease to transition to or from the BRT line. Since the measurement units for each subcomponent variable used to calculate MI varies significantly (as seen in Table 3), the scores are normalized:

(2) $$NS_j = \frac{x_j - \bar{x}_j}{s_j}$$

where the normalized score for each attribute j, NS_j, is calculated as the score, S_j , minus the mean, $\bar{x}_j$, and then divided by the standard deviation, s_j. The normalized scores can be directly compared to assess each category's relative impact on the multimodality index.

The attributes, j, include sidewalk scores, bikeway scores, number of parking spaces, number of transit connections, presence of kiss-n-ride, number of bike spaces, and number of bike lockers. The normalized scores for each station are then inputted into the calculation of the multimodality index. As presented below, the MI is calculated as the sum of the normalized scores, NS_j multiplied by their weights, w_j.

(3) $$MI = \Sigma_j\, w_j\, NS_j$$

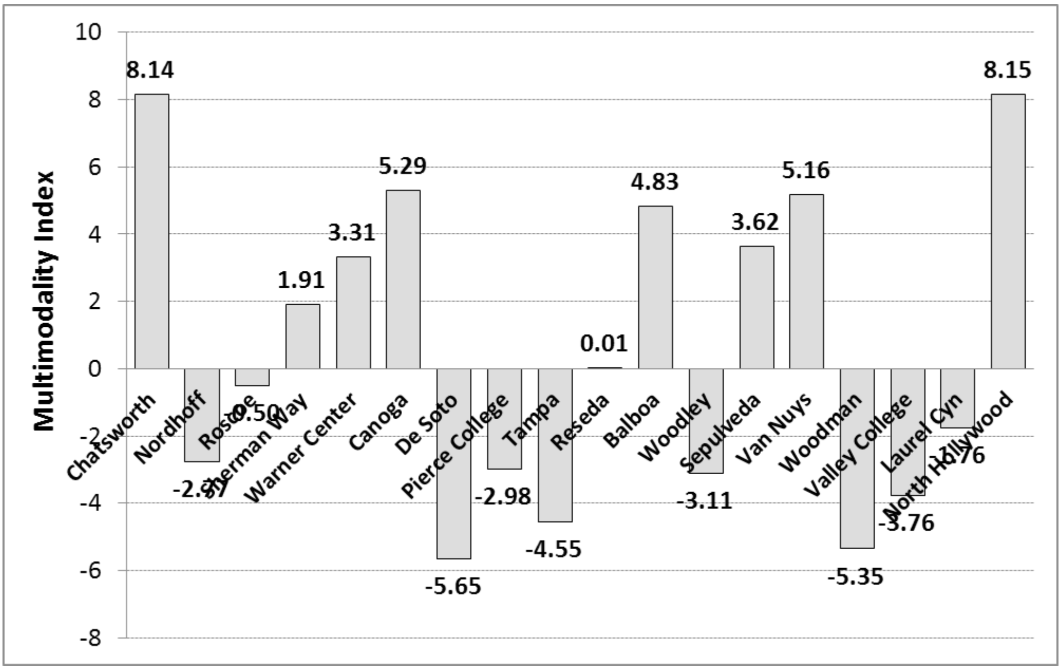
All the weights were set to one, except for the sidewalk quality and public transit connection scores. For these two variables the weight is set to two because they are underrepresented compared with the other modes. Biking has locker, rack, and bikeway quality; auto mode has parking and kiss-n-ride facilities, but walking and transit only have one measure: sidewalk quality and public transit connection scores, respectively. Regression analysis was used to test the effectiveness of the multimodality index as a predictor of ridership while using the control variables shown in Table 4.

ANALYSIS RESULTS

Multimodality Index Results

The multimodality index scores for each Orange Line station are shown in Figure 3. The North Hollywood station has the highest MI, 8.15, indicating the best infrastructure combination to support modal transitions. The De Soto station has the lowest MI, -5.65, because it has neither parking nor kiss-n-ride drop off facilities and has a very low bikeway score. The two terminal stations of the route, Chatsworth and North Hollywood, have the best connectivity (scores of 8.14 and 8.15, respectively), with Metrolink and Red Line subways connections, respectively, and other increased infrastructure. Stations that serve community colleges (Pierce College and Valley College) have low MI scores, so increasing the scores at these stations might increase ridership of a population likely to use transit.

Figure 3: Orange Line Station Multimodality Index Scores



Statistical Analysis: The Effect of Multimodality Index (MI) on Ridership

The Multimodality Index (MI) was designed to assess how multimodal provisions at transit stations influence ridership levels. The index contains several characteristics (subcomponents) of Orange Line BRT stations such as sidewalk quality, overall bikeway quality, bike rack availability, bike locker availability, number of parking spaces, kiss-n-ride availability, and number of regular Metro bus connections. For this study, ridership is defined as boarding at the individual stations for all the months in 2014, except November where data were incomplete, as provided by LA Metro.

To assess the benefits of the MI versus using the individual MI subcomponents, a correlation analysis (including boarding) was conducted. All the subcomponents were statistically significantly correlated with the boarding, but the strongest correlation were with the number of bike lockers, the number of transit connections and the number of parking spaces. The MI was positively and statistically significantly correlated to boarding and all the subcomponents with the higher correlations for sidewalk conditions, the number of parking spaces, and presence of kiss-n-ride (refer Table 5). The MI allows for stations to be designed differently to suit the needs of the surrounding neighborhoods. This creates flexibility for transit operators and the correlation analysis seems to support a strong relationship.

Table 5: Correlation Analysis

	Boarding	MI	Sidewalk	Overall Bike	Bike-rack	Bike locker	No. of space	Kiss-n-ride	Connection
Boarding	1.00								
MI	0.29**	1.00							
Sidewalk	0.15**	0.78**	1.00						
Overall Bike	-0.30**	0.50**	0.20**	1.00					
Bike-rack	-0.22**	0.50**	0.16**	0.63**	1.00				
Bike locker	0.54**	0.43**	0.16**	0.14**	0.11**	1.00			
No. of space	0.39**	0.72**	0.48**	0.12**	0.37**	0.44**	1.00		
Kiss-n-ride	0.21**	0.61**	0.38**	0.17**	0.44**	0.50**	0.74**	1.00	
Connection	0.50**	0.36**	0.27**	-0.24**	-0.32**	0.02*	0.11**	-0.08**	1.00

*(N=1257); *Significance at 0.05 level; **Significance at 0.01 level*

Multivariable linear regression was performed with the MI or each subcomponent as an independent variable to determine the best predictor of boarding while including control variables (density, distance, income, high school availability, the route direction, and month). Because the subcomponents were correlated to each other causing multicollinearity for the regression analysis (refer Table 5), an overall regression with all the subcomponents cannot be performed. This is an advantage of having the MI, which includes all the subcomponents.

The regression results shown in Table 6 demonstrate that MI is the best explanatory variable of ridership, because the adjusted R-squared value (0.41) is higher than most of the subcomponents. The MI and all the control variables are significant at the 99% confidence level. The results of the first regression (with MI as independent variable, excluding the subcomponent variables) indicate that denser areas and stations with high MI have higher ridership; and stations further from downtown, with more high schools and higher income, have lower ridership The unexpected result of high school presence reducing ridership may be due to the significant amount of land they occupy, reducing the density and usage of the transit system.

All the other regression models were also statistically significant at p = 0.01 level. The subcomponent variable was significant for all the models except the bike racks. Bike locker best explained boarding with an adjusted R-squared value of 0.55. The more bike lockers, the more boarding. The control variables had similar results and were statistically significant. In the other model higher sidewalk quality, high transit connection, increased parking spaces, and the presence of kiss-n-ride led to increased transit boarding as expected but with lower adjusted R-squared values (0.31, 0.44, 0.36, and 0.31, respectively). Bikeway quality has a negative beta value indicating an inverse relationship with ridership. This shows that for BRT riders, the station bicycle infrastructure is more important than bicycle infrastructure along the journey to access BRT. Next to bike locker, the MI is the best predictor of transit ridership. It also includes all the subcomponents, which could not be used together in the estimation due to collinearity issues, and therefore a useful tool for transit planning.

The statistically insignificant subcomponent model included the number of bike racks. The number of bike racks was an insignificant variable probably due to cycling transit users' aversion to using bike racks (Olwert et al. 2015) most likely due to weather and theft exposure. This contrasts with the significant variable of the number of bike lockers, where bikes are protected from exposure to weather and theft.

In all the models, Saturday and Sunday boarding were less than the weekdays and were statistically significant. Westbound boarding was also statistically less significant than eastbound. The months were also used in the models but broadly not statistically significant.

Table 6: Regression Analysis Results

	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P	Beta	P
Constant	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00
Distance from Union Station	-0.44	0.00	-0.39	0.00	-0.24	0.00	-0.32	0.00	-0.28	0.00	-0.31	0.00	-0.35	0.00	-0.26	0.00
Log HII	-0.22	0.00	-0.23	0.00	-0.16	0.00	-0.25	0.00	-0.21	0.00	-0.20	0.00	-0.20	0.00	-0.17	0.00
Density	0.25	0.00	0.27	0.00	0.34	0.00	0.30	0.00	0.31	0.00	0.27	0.00	0.31	0.00	0.27	0.00
#of high schools	-0.37	0.00	-0.17	0.00	0.06	0.04	-0.08	0.01	-0.33	0.00	-0.17	0.00	-0.18	0.00	-0.12	0.00
MI	0.45	0.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Sidewalk	-	-	0.18	0.00	-	-	-	-	-	-	-	-	-	-	-	-
Overall Bike	-	-	-	-	-0.32	0.00	-	-	-	-	-	-	-	-	-	-
Bike-rack	-	-	-	-	-	-	-0.04	0.27	-	-	-	-	-	-	-	-
Bike locker	-	-	-	-	-	-	-	-	0.57	0.00	-	-	-	-	-	-
No. of space	-	-	-	-	-	-	-	-	-	-	0.29	0.00	-	-	-	-
Kiss-n-ride	-	-	-	-	-	-	-	-	-	-	-	-	0.19	0.00	-	-
Connection	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.40	0.00
Saturday	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00	-0.17	0.00
Sunday	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00	-0.22	0.00
West	-0.05	0.02	-0.06	0.01	-0.07	0.00	-0.06	0.01	-0.10	0.00	-0.05	0.02	-0.05	0.02	-0.06	0.00
January	-0.02	0.53	-0.02	0.52	-0.03	0.39	-0.02	0.53	-0.01	0.63	-0.01	0.66	-0.01	0.70	-0.03	0.21
February	0.01	0.66	0.01	0.74	0.01	0.87	0.01	0.73	0.02	0.47	0.02	0.56	0.02	0.55	-0.01	0.86
April	0.01	0.77	0.01	0.84	0.00	0.98	0.01	0.83	0.01	0.57	0.01	0.65	0.01	0.64	-0.01	0.75
May	0.01	0.70	0.01	0.77	0.00	0.91	0.01	0.77	0.02	0.50	0.02	0.59	0.02	0.58	-0.01	0.82
June	-0.01	0.85	-0.01	0.81	-0.01	0.66	-0.01	0.82	0.00	0.99	0.00	0.99	0.00	0.99	-0.02	0.41
July	-0.01	0.67	-0.01	0.64	-0.02	0.50	-0.01	0.65	-0.01	0.80	-0.01	0.80	-0.01	0.84	-0.03	0.29
August	-0.01	0.66	-0.01	0.63	-0.02	0.49	-0.01	0.64	-0.01	0.78	-0.01	0.79	-0.01	0.82	-0.03	0.28
September	0.00	0.91	0.00	0.97	0.00	0.88	0.00	0.96	0.01	0.72	0.01	0.78	0.01	0.77	-0.01	0.61
October	0.01	0.83	0.00	0.90	0.00	0.95	0.00	0.89	0.01	0.64	0.01	0.71	0.01	0.70	-0.01	0.68
December	0.00	0.97	0.00	0.97	-0.01	0.83	0.00	0.98	0.01	0.78	0.01	0.84	0.01	0.82	-0.02	0.56
R Square	*0.41*		*0.32*		*0.36*		*0.30*		*0.55*		*0.37*		*0.32*		*0.44*	
Adj. R Square	*0.41*		*0.31*		*0.36*		*0.29*		*0.55*		*0.36*		*0.31*		*0.44*	
F- significance	*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*		*0.00*	
Dependent variable: Station boarding for the year 2014. N=1257. Data source: LA Metro																

DISCUSSION AND CONCLUSION

The multimodality index provides objective scores of multimodal access to each Orange Line stations. Because the MI calculations use normalized data, the MI is a relative measure that compares stations in a given study, the Orange Line in this case. By comparing the MI scores across the stations, planners can identify stations on the Orange Line that are potentially underserved and subcomponents that might increase ridership. Increased multimodal accessibility provides convenient alternatives to Los Angeles' primary commute mode: the automobile. The MI identifies stations that have poor access, providing insight to transit agencies.

The correlation and regression analysis supports the MI as a reliable predictor of ridership, but allows transit agencies flexibility in deciding how to increase the MI score. Different combinations of facilities can still produce a similar MI score. A station with abundant parking can have the same MI score as a station with less parking but more biking and pedestrian facilities. Transit planners should increase MI scores by providing facilities that the station types need. A residential station may require more parking while an employment center station may require better pedestrian quality and more transit connections. This has, in fact, been implemented in part along the Orange Line. Terminus stations and stations with industrial and employment activities have higher MI scores because of their better walking and biking facilities and increased transit connections. However, the residential stations that have high MI have abundant parking. Thus, it is recommended that multimodal infrastructure be provided based on the neighborhood characteristics surrounding the station.

The correlation and regression analysis suggests that bike lanes and bike racks, when assessed independently, are not significant in affecting ridership. This contradicts the literature (USDOT-FHWA 1992; Nelson and Nygaard 2009), and may be a result of the short buffer zones used (100 ft). A quarter mile would be recommended as a more reasonable length for similar studies. However, as part of the overall MI, the bicycle components are still important.

The MI could be used to compare individual stations across regions or even between regions. Using a random sample of stations across a large area, the normalization mechanism would allow for comparison of a particular station to the greater population of stations. The MI score for a particular station could be compared with the median MI to provide insight on useful upgrades.

References

Bielli, M., A. Boulmakoul, and H. Mouncif. "Object Modeling and Path Computation for Multimodal Travel Systems." *European Journal of Operational Research* 175(3), (2006): 1705–1730.

Cain, A., G. Darido, M. R. Baltes, P. Rodriguez, and J. C. Barrios. "Applicability of TransMilenio Bus Rapid Transit System of Bogotá, Colombia, to the United States." *Transportation Research Record: Journal of the Transportation Research Board 2034*(1), (2007): 45-54.

Cervero, R., "Bus Rapid Transit (BRT): An Efficient and Competitive Mode of Public Transport." *Working paper 2013-01*, California University Los Angeles, 2013.

Cervero, R., and K. Kockelman. "Travel Demand and the 3Ds: Density, Diversity, and Design." *Transportation Research Part D: Transport and Environment* 2 (3), (1997): 199–219.

Dewitt, W. and J. Clinger. *Intermodal Freight Transportation. Transportation in the New Millennium*. Transportation Research Board (TRB), 2000.

Dilger, R. "ISTEA: A New Direction for Transportation Policy." *Publics: The Journal of Federalism* 22(3), (1992): 67-78.

Dill, J., M. Schlossberg, L. Ma, and C. Meyer. "Predicting Transit Ridership at Stop Level: Role of Service and Urban Form." Paper presented at the 92nd Annual Meeting of the Transportation Research Board 2013.

Dill, J. "Measuring Network Connectivity for Bicycling and Walking." Paper presented at Transportation Research Board Annual Meeting, 2004.

Duarte, F., and F. Rojas. "Intermodal Connectivity to BRT: A Comparative Analysis of Bogotá and Curitiba." *Journal of Public Transportation 15*(2), (2012): 1-18.

Evans J. "Traveler Response to Transportation System Changes: Chapter 9-Transit Scheduling and Frequency" TCRP #95, Transportation Research Board, 2004.

Frank A. U. "Shortest Path in a Multi-Modal Transportation Network: Agent Simulation in a Product of Two State-Transition Networks." *KI Künstliche Intelligenz* 3, (2008): 14-18.

Frank, L., J. Chapman, M. Bradley, and T. K. Lawton. *Travel Behavior, Emissions & Land Use Correlation Analysis in the Central Puget Sound.* Prepared for the Washington State Transportation Commission, 2005.

Godefrooij, T., C. Pardo, and L. Sagaris. *Cycling-Inclusive Policy Development: A Handbook*. German Technical Cooperation (GTZ), 2009.

Guttenplan, M., and S. Reynolds. "Measuring Multimodal Mobility with the 'Highway Capacity Manual' 2010 and Other New Analysis Tools." *Transportation Research Board* 280, (2012): 46-52.

Hidalgo, D., and A. Carrigan. "Modernizing Public Transportation: Lessons Learned from Major Bus Improvements in Latin America and Asia." World Resources Institute, Washington DC, 2010.

Hochmair, H. "Grouping of Optimized Pedestrian Routes for Multi-Modal Route Planning: A Comparison of Two Cities." Bernard L., Friis-Christensen A. and Pundt H. eds.*The European Information Society*, Berlin Heidelberg: Springer (2008): 339–358.

Institute for Transport and Development Policy (ITDP). *Bus Rapid Transit Standards*. New York, 2014.

Iseki, H., M. Miller, A. Ringler, M. Smart, and B. D. Taylor. "Evaluating Connectivity Performance at Transit Transfer Facilities." University of California, Los Angeles, 2007.

Kerman, K., K. Martens, and H. Meurs. "Factors Influencing Stop Level Transit Ridership in the Arnhem Nijmegen City Region." TRAIL Research School, November 2014.

Kolko, J. "Making the Most of Transit Density, Employment Growth, and Ridership Around New Stations" Public Policy Institute of California, 2011.

Keshkamat, S., J. Looijen, and M. Zuidgeest. "The Formulation and Evaluation of Transport Route Planning Alternatives: A Spatial Decision Support System for the Via Baltica Project, Poland." *Journal of Transport Geography* 17(1), (2009): 54-64.

Levinson, H.S., and R.A. Weant. "Transportation and Parking Demand Analysis for Bridgeport Intermodal Transportation Center." Prepared for Wallace Floyd Design Group, Boston, MA, 2000.

Litman, T. "Introduction to Multi-Modal Transportation Planning." *Victoria Transport Policy Institute*, 2014.

Liu, L. "Data Model and Algorithms for Multimodal Route Planning with Transportation Networks*."* Doctoral Dissertation, München, Techn. University, 2011.

Mahrous, R.F. "Multimodal Transportation Systems: Modelling Challenges." Master's Thesis. University of Twente, 2012.

Martens, K. "Promoting Bike-and-ride: The Dutch Experience." *Transportation Research A* 41(4), (2007): 326-338.

Moudon, A. V., P. Hess, M.C. Snyder, and K. Stanilov. "Effects of Site Design on Pedestrian Travel in Mixed-Use, Medium-Density Environments." *Transportation Research Record* 1578, (1997): 48–55.

Neff, J. *A Profile of Public Transportation Passenger Demographics and Travel Characteristics Reported in On-Board Surveys*. American Public Transportation Association (APTA), 2007.

Nelson\Nygaard Consulting Associates. "Maximizing Mobility in Los Angeles: First & Last Mile Strategies." A report for Southern California Association of Governments (SCAG), 2009.

Nobis, C. "Multimodality: Facets and Causes of Sustainable Mobility Behavior." Paper presented at TRB Annual meeting, 2006.

Olwert, C., J. Tchopourian, V. Arellano, and M. Woldeamanuel. "Stranding Cycling Transit Users on Los Angeles' Orange Line Bus Rapid Transit." *Journal of Public Transportation 18*(1), (2015):1-15.

Polat, C. "The Demand Determinants for Urban Public Transport Services: A Review of the Literature." *Journal of Applied Sciences* 12(12), (2012): 1211-1231.

Rickert, T. "Technical and Operational Challenges to Inclusive Bus Rapid Transit: A Guide for Practitioners." World Bank, Washington*,* 2010.

Scheurer, J., and C. Curtis. "Spatial Network Analysis of Multimodal Transport Systems: Developing a Strategic Planning Tool to Assess the Congruence of Movement and Urban Structure: A Case Study of Perth Before and After the Perth-to-Mandurah Railway." GAMUT, Australasian Centre for the Governance and Management of Urban Transport, University of Melbourne, 2008.

Strate, H. E., E. Humstone, S. McMahon, L. Gibson, and B. Bender. "Functional Classification for Multimodal Planning." *Transportation Research Record: Journal of the Transportation Research Board 1606*(1), (1997):51-62.

Talbott, M. “Bus Stop Amenities and their Relationship with Ridership: A Transportation Equity Approach.” Thesis (M.A.), The University of North Carolina at Greensboro, 2011.

USDOT-FHWA. *Linking Bicycle/Pedestrian Facilities with Transit Enhancing Bicycle and Pedestrian Access to Transit*. FHWA-PD-93-012, 1992.

Vincent, W., and L. C. Jerram. “The Potential for Bus Rapid Transit to Reduce Transportation-Related CO2 Emissions.” *Journal of Public Transportation 9*(3), (2006): 219-237.

Waddell, P., and F. Nourzad. “Incorporating Nonmotorized Mode and Neighborhood Accessibility in an Integrated Land Use and Transportation Model System.” *Transportation Research Record: Journal of the Transportation Research Board* 1805(1), (2002): 119-127.

Woldeamanuel, M. “Younger Teens Mode Choice for School Trips: Do Parent’s Attitudes Towards Safety and Traffic Conditions Along the School Route Matter?” *International Journal of Sustainable Transportation* 10(2), (2014): 147-155.

Wright, L., and L. Fulton. “Climate Change Mitigation and Transport in Developing Nations.” *Transport Reviews 25*(6), (2005):691-717.

Mintesnot G. Woldeamanuel *is an associate professor of urban studies and planning at California State University, Northridge, where he conducts research on transportation planning and multimodal travel.*

Craig T. Olwert *is an assistant professor of urban studies and planning at California State University, Northridge, where he conducts research on sustainability, transit-oriented development, economic development, and retail planning.*

Effective Light Source for Illuminating Overhead Guide Signs and Improving Roadway Safety

by Mohammed S. Obeidat, and Malgorzata J. Rys

Driver safety is considered an important issue to departments of transportation. One way to increase highway safety is to improve the visibility of overhead guide signs for drivers. Visibility improving methods include the use of sign illumination or retroreflective sheeting materials. This paper focuses on sign illumination by comparing five light sources including high pressure sodium (HPS), metal halide (MH), mercury vapor (MV), induction lighting, and light emitting diode (LED). A laboratory experiment was conducted to compare effective light distribution of each light source and a cost analysis was performed to compare initial, maintenance, and operating cost components of the light sources. Results of the light distribution experiment indicated that HPS was the optimum light source followed by MH, induction lighting, MV, and LED. Induction lighting is a promising lighting technology which features good efficiency and long life. According to cost analysis, induction lighting was the most effective source, followed by the LED, HPS, MV, and MH. Of the five light sources considered, induction lighting provided the best overall performance when considering initial cost, operating cost, expected maintenance, and sign illuminance. Environmentally, LED does not contain mercury, and for those agencies that prefer using sources that are friendlier with the environment, the LED can be their best choice.

INTRODUCTION

Motor vehicles are important modes of transportation worldwide. To safely operate a motor vehicle, however, drivers must simultaneously utilize various skills and perform multiple tasks while accounting for factors such as other roadway users, traffic signals, signs, and environment (Dukic and Broberg 2012). Based on road statistics, the most important driving skills include the acquisition and processing of information and the ability to make appropriate decisions when needed (Dewar and Olson 2007).

One primary mission of the Federal Highway Administration (FHWA) in the U.S. is to increase roadway safety. According to the National Highway Traffic Safety Administration's (NHTSA) Fatality Analysis Reporting System (FARS), 32,719 people were killed in motor vehicle traffic crashes in the U.S. in 2013 (NHTSA 2014). Statistics show that 25% of all motor vehicle travel occurs at night, but approximately 50% of all traffic fatalities occur during nighttime hours (FHWA 2008).

Guide signs in U.S. are typically green and are located along a roadway to notify drivers of destinations and exit information. Overhead guide signs, which are essential for driver guidance, have the primary objective of providing drivers with information regarding destinations.

As required in the Manual on Uniform Traffic Control Devices for Streets and Highways (MUTCD), overhead guide signs must be illuminated or manufactured from retroreflective sheeting materials (FHWA 2009). Departments of transportation (DOTs) in the U.S. must consider whether to add light sources to overhead guide signs currently installed on highways, or add modern retroreflective sheeting material to these signs, to improve sign visibility for drivers during nighttime, thereby possibly reducing potential accidents due to driver confusion.

This paper consists of three phases to evaluate light sources used to illuminate overhead guide signs: laboratory experiment to compare five light sources, cost analysis of the tested light sources, and testing light sources for toxic materials contents. The laboratory experiment was conducted to compare light distribution of five light sources. These light sources include metal halide (MH), mercury vapor (MV), high pressure sodium (HPS), induction lighting, and light emitting diode (LED) that produces white color. A cost analysis was also performed to compare the five light sources based on initial maintenance and operating costs during the lifespan of each light source. Because of the presence of toxic materials in the studied light sources such as lead and mercury, except for the LED, which is free of lead and mercury, environmental-related issues were considered as additional decision criterion when comparing light sources. The objective of this paper was to determine the most effective light source to be used by DOTs to improve overhead guide sign visibility during nighttime. Determination was made based on three decision criteria: light distribution, average annual cost, and environmental-related issues of light sources. Light distribution refers to the values of the luminous intensities radiated in all relevant directions by the luminaire. Luminaire refers to a complete electric light unit. In this paper, the luminous intensities that fall on a sign will be considered to evaluate the light distribution of different light sources.

LITERATURE REVEW

Drivers of all ages often experience more difficulty driving at night compared with daytime driving. Visibility issues include driver's visual acuity, contrast sensitivity, distance judgment, and color discrimination (Lagergren 1987). Roadway lighting is a basic public amenity that contributes to a safer environment for drivers and pedestrians. Efficient roadway lighting can improve personal security, traffic flow operations, and safety because drivers can more clearly recognize street conditions and geometry of the roadway (Medina et al. 2013).

Guide signs must be visible and clear for intended drivers in order to allow for suitable driving response time. In fact, "overhead highway signs must be highly visible and legible so that drivers can detect, read and interpret the information contained on the signs in time to respond appropriately" (Bullough et al. 2008). Desirable attributes for guide signs include high visibility and legibility during day and night. Legibility is defined as "the readability of a particular writing style, or font" (Amparano and Morena 2006).

Traveling on U.S. roadways can be confusing and challenging for drivers if driving routes are not easily understood or clearly marked, especially when the driver is unfamiliar with the driving location (Amparano and Morena 2006). Travelling can be challenging for older drivers, age 65 and older, especially those older drivers who have cognitive or physical disabilities (Amparano and Morena 2006). However, various engineering improvements, such as sign placement, legibility of sign lettering, sign illumination, retroreflectivity, and sign size, can increase the probability that a driver will detect signs and comprehend sign messages.

Overhead guide signs can be illuminated from the back, known as back-illuminated, or by utilizing external light sources to illuminate the sign face (Bullough et al. 2008). External light sources are light fixtures designed to illuminate overhead guide signs by transforming electrical power into a visible light. Another way of illuminating overhead guide signs is by using luminous sources or elements, such as LED, to produce required sign characters (Bullough et al. 2008).

Retroreflective sheeting materials can also be used to enhance overhead guide sign visibility for drivers. Obeidat et al. (2014) performed a study to find DOTs' policies for increasing the visibility of overhead guide sign on highways. They found that the most commonly used retroreflective sheeting material by states for overhead guide sign legend is Diamond Grade (type IX followed by type XI), and High Intensity (types III and IV) for sign background. Obeidat et al. (2015) in another study compared three retroreflective sheeting used by DOTs for overhead guide sign: Engineering Grade (type I), High Intensity (type IV), and Diamond Grade (type XI). The comparison was based on results of a field experiment involving human participants and a cost analysis. They recommended DOTs use high intensity (type IV) retroreflective sheeting for guide signs since it increases visibility and consequently increases safety.

Light sources associated with little short-wavelength light are less effective for vision than light sources that produce greater short-wavelength (blue), even if the measured light level is similar, because of the human eye's shifted response to light at some nighttime light levels. This is true for certain locations in the field of view and for certain light levels (Bullough 2012a). One wavelength of light represents the distance between two consecutive corresponding points of one wave. Wave in physics is defined as any regularly recurring event. *Waves* are characterized by wavelength, frequency, and the speed at which they move. Several light sources used for roadway illuminating devices are available in the market. These light sources are classified into conventional or traditional lighting and new light source generation. Conventional lighting includes incandescent lamps and electric discharge lamps, and new light source generation includes induction lighting and LED.

Conventional Light Sources

In incandescent lamps, an electrical current passes through a wire and the wire heats to a certain level, causing the wire to glow and emit light (Lopez 2003). According to Lopez (2003), tungsten halogen and common incandescent are two prominent types of incandescent lamps. Tungsten halogen (quartz iodide) is not used for roadway lighting (Lopez 2003). The common incandescent lamps consist of a tungsten filament enclosed in a glass envelope that is attached to a metal base. The bulb is evacuated first (all gases and other materials are removed) and then inert gas (usually nitrogen or argon) is introduced into the bulb to increase bulb life and efficiency. The common incandescent lamp has low initial and operating costs, but it also has low efficacy (lumens per watt) and a short lifespan ranging between 1,000-2,000 hours (BITS 2012). One disadvantage of incandescent lamps is that they contain some toxic materials such as lead and mercury, which makes them non-environmentally friendly (California Department of Toxic Substances Control 2010).

According to Lopez (2003), five common types of electric discharge light sources are: fluorescent, induction fluorescent, MV, HPS, low pressure sodium (LPS), and MH (Lopez 2003).

Based on Lopez (2003), fluorescent lamps contain mercury to produce a mercury arc which operates at low vapor pressure to produce ultraviolet light. The mercury arc in fluorescent lamps is produced when an electric current excites the mercury vapor, which works at low pressure to produce ultraviolet light. The ultraviolet light strikes a phosphor coating the bulb, which causes visible light to be emitted. Fluorescent light sources have a moderate initial cost, long lifespan, and high efficacy (30-70 lumens/watt). However, since fluorescent lamps contain mercury, they are not environmentally friendly.

Induction fluorescent lamps have the same principle as fluorescent lamps except that they do not have a tubular shape (Lopez 2003). Some types of induction fluorescent lamps have a high efficacy (up to 75 lumens/watt) with extremely long lifespan (up to 100,000 hours). Induction fluorescent is suitable for low-mounting heights. However, induction fluorescent is non-environmentally friendly because it contains toxic materials such as lead and mercury (California Department of Toxic Substances Control 2010).

MV light sources contain a quartz arc tube with a mercury arc which produces visible light and ultraviolet light. The glass envelope of the MV light sources helps filter some of the far ultraviolet light (Lopez 2003). Two types of MV are available in the market: clear light and phosphor-coated light. MV light sources that include phosphor-coated light are used for sign lighting. Advantages of MV light include relatively long lifespan and high efficacy (30-65 lumens/watt). One disadvantage of MV is the presence of mercury, consequently causing the MV light source to be non-environmentally friendly. The MV is no longer available in the U.S. market because of the Energy Independence and Security Act (EISA) of 2007.

In the HPS light source, light is produced by an arc in a ceramic tube containing sodium and other elements to improve color rendition (Lopez 2003). Advantages of HPS light include relatively low initial cost, long useful life, high efficacy (45-150 lumens/watt), and the ability to maintain relatively high light output throughout the lifespan (Bullough 2012b). One disadvantage is that most HPS light sources contain toxic materials, such as mercury, which makes those HPS types non-environmentally friendly (Recycle SD Inc. 2014).

In the LPS light source, light is produced by an arc tube (gas discharge tube) in a long glass envelope that only contains sodium in order to produce a yellow light with poor color rendering (Lopez 2003). Advantages of LPS include moderately long lifespan and high efficacy (145-185 lumens/watt). Most of LPS light sources are non-environmentally friendly because they contain mercury (Recycle SD Inc. 2014).

MH light source is similar to the MV light source, but in addition to mercury, it contains various metal halides which provide excellent color rendering, resulting in white light (Lopez 2003). MH light sources have been available for several decades, and recent technology has increased efficacy of MH sources, increased the useful life, and improved lumen maintenance (Bullough 2012b). Lumen maintenance refers to the comparison between the amount of light produced from a light source when it is brand new to the amount produced after using the light source for a period of time. New MH light sources that have ceramic arc tubes and modern source starting methods have increased efficiency, lifespan, and lumen maintenance. One disadvantage of MH is the presence of mercury, rendering it non-environmentally friendly.

New Generation of Light Sources

Unlike conventional fluorescent lamps that have electrodes at either end of the lamp tube, induction lighting uses radio frequencies to stimulate lamp material to produce light (Bullough 2012b). Induction lamps, however, use radio frequency or microwaves to create induced electrical fields which excite gases to produce light. Induction lamps manifest the same color as conventional fluorescents and share their diffuse appearance, but induction lamps do not require the longer tubular shape of most fluorescent sources. Diffused light is non-directional light, where the light has an even intensity. Induction lighting is a lighting technology with efficacy and lifespan advantages over conventional lighting (Deco Lighting 2010).

Induction light source manufacturers claim that induction light sources have rapid start-up and operates at peak efficiency with minimal warm-up time. Disadvantages of induction lighting include limited directionality of light beams and inability to focus compared with LEDs, hazardous lead, and mercury, which require special handling for disposal, inability to function efficiently in cold environments, production of ultraviolet (UV) radiation which harms products such as retroreflective sheeting, and delayed adoption of induction-based roadway lighting systems, which is already in its peak of improvement because of rapidly improving LED technology (Deco Lighting 2010 and GRAH Lighting 2014).

Recent technologies and advances in solid-state lighting have resulted in an LED light source that produces white light. This light is produced by short wavelength LEDs that create blue light which, when combined with phosphor, converts the blue light into yellow light, resulting in a white mixture (Bullough 2012b). LED-based roadway lighting products offer several advantages over traditional lighting technologies. Modern LED light sources used for street and sign lighting are also free of mercury and are compliant with Restriction of Hazardous Substances (RoHS) (Tri-State LED 2012). However, a study performed by Lim et al. (2010) showed that some LEDs contain other toxic materials such as lead, arsenic, and phosphorus, which make them not environmental friendly. Based on Lim et al. (2010), LEDs that produce white light color are free of mercury, lead, arsenic, barium, gadolinium, indium, tungsten, and yttrium. The unique environmental advantage of all LED types, no matter the produced light color, is that they do not contain mercury (Lim et al. 2010).

The LED light source for roadway lighting also meets the American Association of State Highway and Transportation Officials' (AASHTO) requirements published in 2005 with approximately 7% reduction in energy use. An energy savings of 30% to 50% can be achieved by replacing HPS with

LED or induction lighting in residential areas, and 35% to 40% by replacing HPS with LED or induction lighting at rural intersections where peripheral visibility is essential (Bullough 2012b).

Advantages of LEDs include low energy consumption, long lifespan, high color quality, improved performance in Mesopic vision conditions (Mesopic vision is defined as the light levels at which cones and rods contribute to human vision [Avrenli et al. 2012], where in the human retina there are two types of photoreceptors: rods and cones), instant lighting, small compact size, directional light, light pollution reduction, environmentally friendly characteristics, dimming capabilities, free of mercury and vibration, and breakage resistance. However, LED disadvantages include high maintenance cost, less luminous efficacy than conventional light sources, heat conversion rate (LEDs have a higher rate of electric power to heat conversion), issues in obtaining white light, and problems associated with the LED module arrays such as increasing failure chance of a component when the number of used LED chips (a semiconductor chip) increase, individual LEDs overdriving in the array when LEDs start to fail (when an LED fails, the remaining LEDs will be driven harder, therefore, the temperature will be increased and the life of the system will be reduced), and leading to multiple shadows (Avrenli et al. 2012). LEDs can be used to illuminate roadways only if numerous LED chips are incorporated together into a module of LED, and then several LED modules are incorporated into an LED module array (Avrenli et al. 2012). Additional details of LED's advantages and disadvantages can be found in Avrenli et al. 2012.

Light Sources Comparison

Table 1 shows a comparison summary of the light sources included in the literature review section, and can be used to illuminate overhead guide signs on roadways.

Table 1: Light Sources Comparison

Light Source	Lighting Category	Efficacy (lumens/watt)	Lifespan	Toxic Materials Contents
Common incandescent	Conventional	Low	Short	Lead and mercury
fluorescent lamps	Conventional	High	Moderate	Mercury
Induction fluorescent	Conventional	High	Long	lead and mercury
MV	Conventional	High	Long	Mercury
HPS	Conventional	High	Long	Mercury
LPS	Conventional	High	Long	Mercury
MH	Conventional	High	Long	Mercury
Induction lighting	New generation	High	Very long	Lead and mercury
LED	New generation	High	Very long	None

METHODOLOGY

The first phase of this research was the light distribution experiment. A laboratory experiment was conducted to evaluate light distribution of five light sources used for overhead guide sign illumination. The purpose of the experiment was to determine optimal light distribution for each of the five light sources and identify which light source provides the most efficient illuminance on the sign. The optimal light distribution of a luminaire is the best distribution of light intensity on a sign. The studied light sources and their fixtures' specifications are shown in Table 2. The LED type that was used in this experiment was producing white color and designed for sign's lighting.

Table 2: Light Sources and Fixtures Specifications

Light Source	Fixture specifications
The 250 watt MH	Consists of aluminum reflector that contours the light source to distribute light through a borosilicate glass refractor. Borosilicate glass is a low-melting glass produced from a mixture of boric oxide and silica. For maximum efficiency and uniformity, precisely cut prisms direct the light onto the billboard.
The 250 watt MV	Consists of aluminum reflector that contours the light source to distribute the light through clear and tempered glass which is resistant to heat and shock, along with convex-shaped glass lens made from borosilicate.
The 250 watt HPS	Consists of die-cast aluminum housing with electro-coat paint finish. It has clear thermal and impact resistant tempered glass, and convex borosilicate glass lens.
The 85 watt induction lighting	Consists of hydro-formed aluminum reflector that contours the light source to distribute light through a borosilicate glass refractor. For maximum efficiency and uniformity, precisely cut prisms direct the light onto the billboard.
The 62 watt LED	Consists of three adjustable arrays, each containing eight LEDs. The fixture is associated with all-weather marine aluminum, glass diffuser, and stainless steel fastener. Adjustable arrays mean that the rod where the LEDs are attached can be adjusted or rotated.

The second phase of the paper was to conduct a cost analysis for the five light sources, including initial cost, operating cost, and maintenance cost. In the last phase, the presence of toxic materials in the light source and its energy consumption were considered as environmental issues. Finally, results of the light distribution experiment are corroborated with results of the cost analysis and environmental-related issues to determine the most cost-effective light source to illuminate overhead guide signs to increase illuminance on the sign, which contributes to better sign visibility for drivers and consequently better roadway safety.

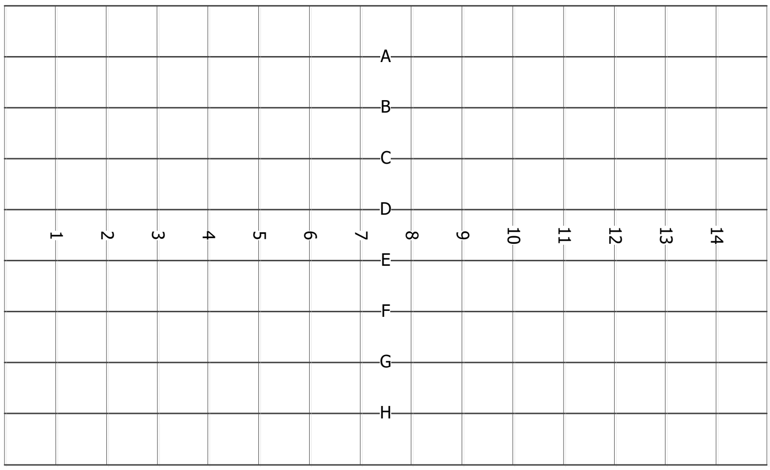
LIGHT DISTRIBUTION EXPERIMENT

Setup and Procedure

The current experiment was conducted in the workshop of the Industrial and Manufacturing Systems Engineering Department at Kansas State University, Manhattan, Kansas. Black cardboard covered all windows, and the emergency light in the room was turned off to ensure complete darkness. A white sheet of paper, 15 ft. wide and 9 ft. high, mounted to the wall represented an overhead guide sign of similar size. The Kansas Department of Transportation (KDOT) had established a standard horizontal distance between the light source unit and sign to be 5-6.5 ft. In this experiment, the light source unit was centered in front of the sign on the floor at a horizontal distance of 5 ft. from the white sheet on the wall to the nearest edge of the light source.

A grid of 1-ft. increments was marked on the sheet of paper, as shown in Figure 1. At a height of 8 ft. from the top of the opposing light source on the floor, the horizontal line on the paper was named row “A” and the line at a height of 1 ft. was row “H.” Similarly, the vertical line at the left side of the paper was named column “1” and the vertical line on the right side was column “14.”

Figure 1: Grid on White Paper



A Minolta illuminance meter measured illuminance in lux (which is the International System [S.I.] unit of illuminance) at each grid line intersection (row-column intersection) beginning at the top row (row A), left side of the white sheet of paper (column 1), to the bottom right side. Three illuminance measurement readings were taken at each intersection and the average was calculated at each intersection point after removing any outlier. The unit of measurement for illuminance is lux, and each lux is equivalent to lumen/meter^2. Illuminance can also be measured by foot-candle, which is lumen/foot^2. When running the experiment, each light source was given a suitable warming period by being turned on at least 45 minutes before commencing illuminance readings to ensure that the light source would run at maximum luminance output. In addition, the Minolta illuminance meter was calibrated before beginning each experimental run.

For the 250 watt MH light source, the unit was placed in front of the white paper at four angles measured between the bottom of the light source unit and the floor. These angles were 0^o, 5^o down, 10^o down, and 15^o down. Similarly, for the 250 watt MV light, the unit was placed in front of the white paper at angles 0^o, 5^o up, 5^o down, and 10^o down. For the 250 watt HPS light source, the light source unit was set in front of the paper at 0^o angle only because the output illuminance was very high. For the 250-watt induction light, the angles were 0^o, 5^o down, 10^o down, and 15^o down. Finally, for the 62 watt LED light source, the light source unit was placed in front of the white paper at a 0^o angle because the design of this LED includes independent and adjustable LED arrays (or LED module arrays). The purpose of studying various angles was to identify at what position the light source provides higher illuminance on the sign.

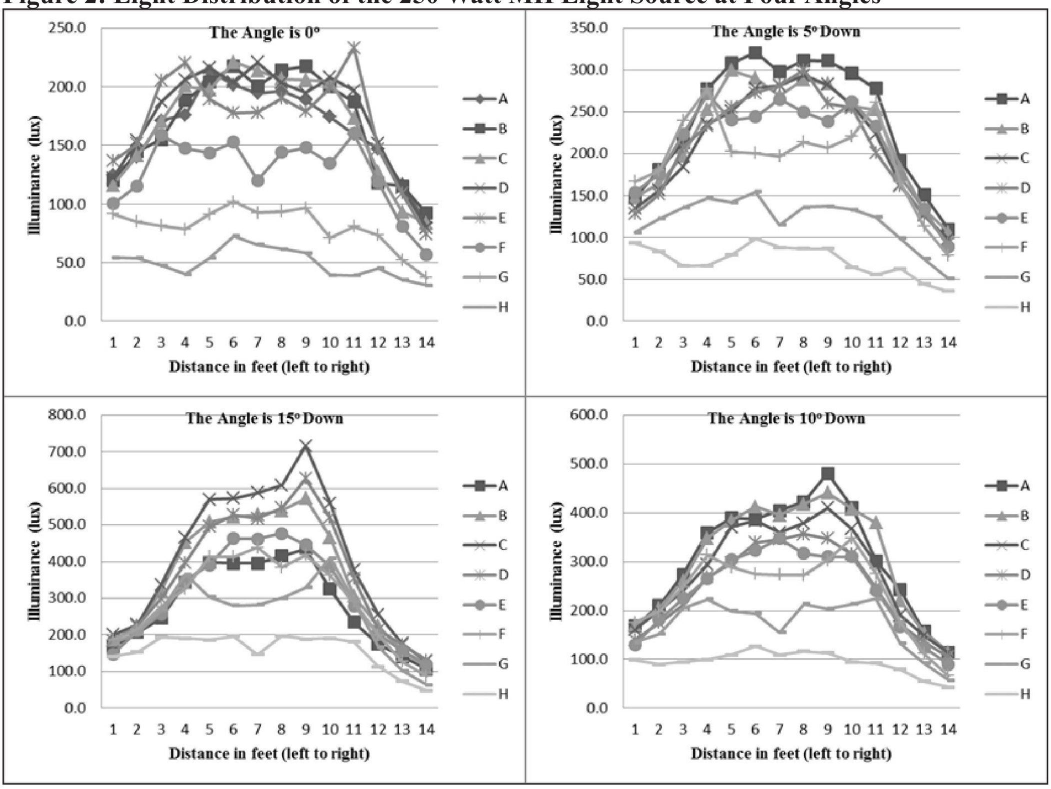
RESULTS AND DISCUSSION

Since some light sources were tested at more than one angle, illuminance values at each row-column intersection of the white paper were compared for each light source in order to determine the angle at which light distribution produced maximum illuminance values. This section of the paper compares light distribution for each light source at various angles and compares optimum light distribution for each light source at the selected angle with other sources' optimum light distribution, to determine which source provided optimum light distribution and increased illuminance on the sign that contributes to better visibility for drivers and higher safety during nighttime.

Finding Optimum Light Distribution for Each Light Source

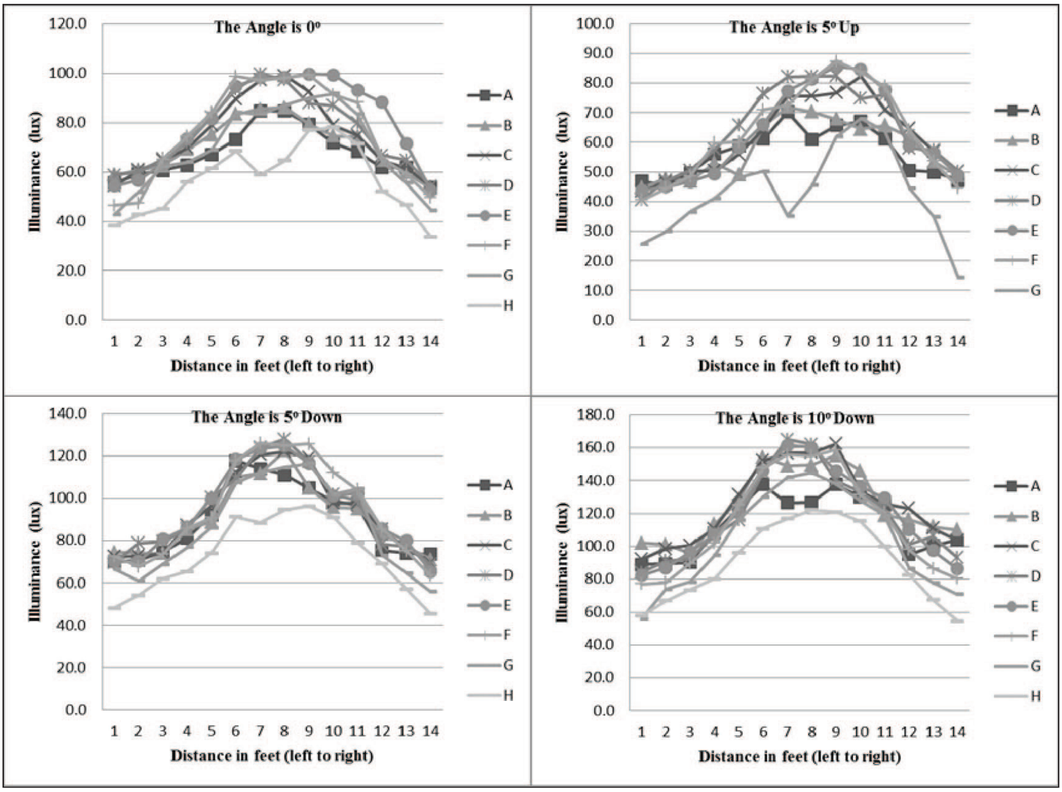
The MH Light Source. Light distribution of the 250 watt MH light source at four angles is shown in Figure 2. Based on results in that figure, the optimum light distribution of the 250 watt MH light source was when the angle between the bottom of the light source unit and the floor was 15° down. Light distribution at 15° down appeared to be uniform and illuminance values range between 200-600 lux, approximately. These illuminance values are comparatively high and might cause light pollution, and may not provide high visibility to drivers. Light pollution is defined as brightening of the night sky from street lights and other light sources, which inhibits the observation of stars and planets and has a disruptive effect on natural cycles.

Figure 2: Light Distribution of the 250 Watt MH Light Source at Four Angles



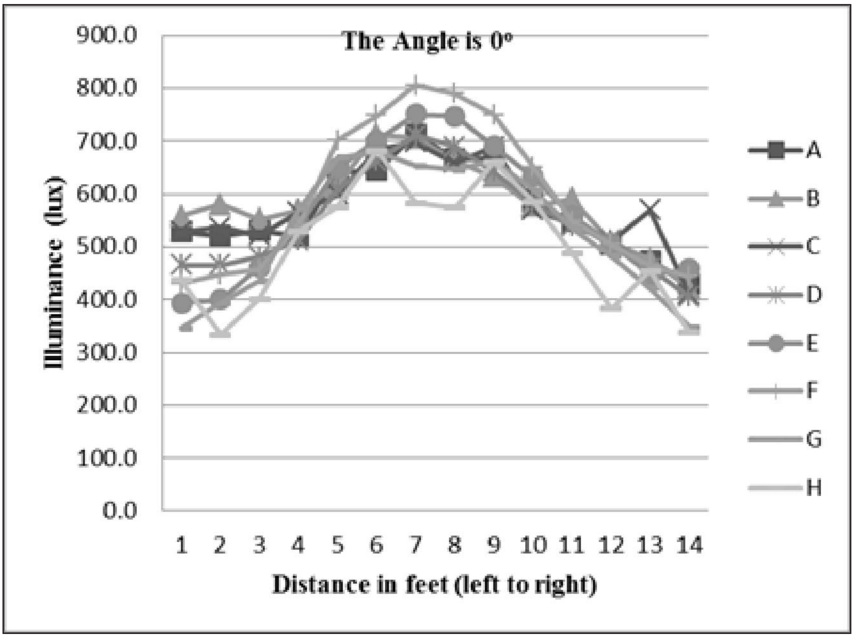
MV Light Source. Light distribution of the 250 watt MH light source at four angles is shown in Figure 3. Based on results shown in that figure, the optimum light distribution of the 250 watt MV light source was when the angle between the bottom of the light source unit and the floor was 10° down. Light distribution at 10° down appeared to be uniform, and illuminance values range between 70-160 lux, approximately.

Figure 3: Light Distribution of the 250 Watt MV Light Source at Four Angles



HPS Light Source. Light distribution of the 250 watt HPS light source at 0° angle is shown in Figure 4. Light distribution for HPS at 0° angle was considered the optimum because measured illuminance values were very high, consequently allowing motorists to see the guide sign because of increased illuminance on the sign. Light distribution appeared to be uniform and illuminance values range between 400-800 lux, approximately. These illuminance values are comparatively very high, and might cause a light pollution.

Figure 4: Light Distribution of 250 Watt HPS Light Source at 0° Angle



Induction Light Source. Light distribution of the 85-watt induction lighting at different angles is shown in Figure 5. Based on results shown in that figure, the optimum light distribution of the 85-watt induction light source occurred when the angle between the bottom of the light source unit and the floor was 15° down. Light distribution appears to be uniform at 15° down and illuminance values range between 110-300 lux, approximately.

LED Light Source. The 62W LED light source was placed in front of the white paper at 0° angle because the design of this LED includes independent and adjustable LED arrays. By rotating these arrays, LED light can be focused toward any direction on the sign. The manager of this LED manufacturer asserted that this LED was ready for installation because the LED array angles were appropriately fixed to focus light along a sign similar to the white paper in the experiment. Light distribution of the 62 watt LED light source at 0° angles is shown in Figure 6. The optimum light distribution of the 62W LED light source occurred when the angle between the bottom of the light source unit and the floor was 0°. Light distribution appeared to be uniform and illuminance values range approximately between 20-165 lux. Light distribution of the 62 watt LED light source demonstrated low illuminance values.

Figure 5: Light Distribution of the 85 Watt Induction Light Source at Four Angles

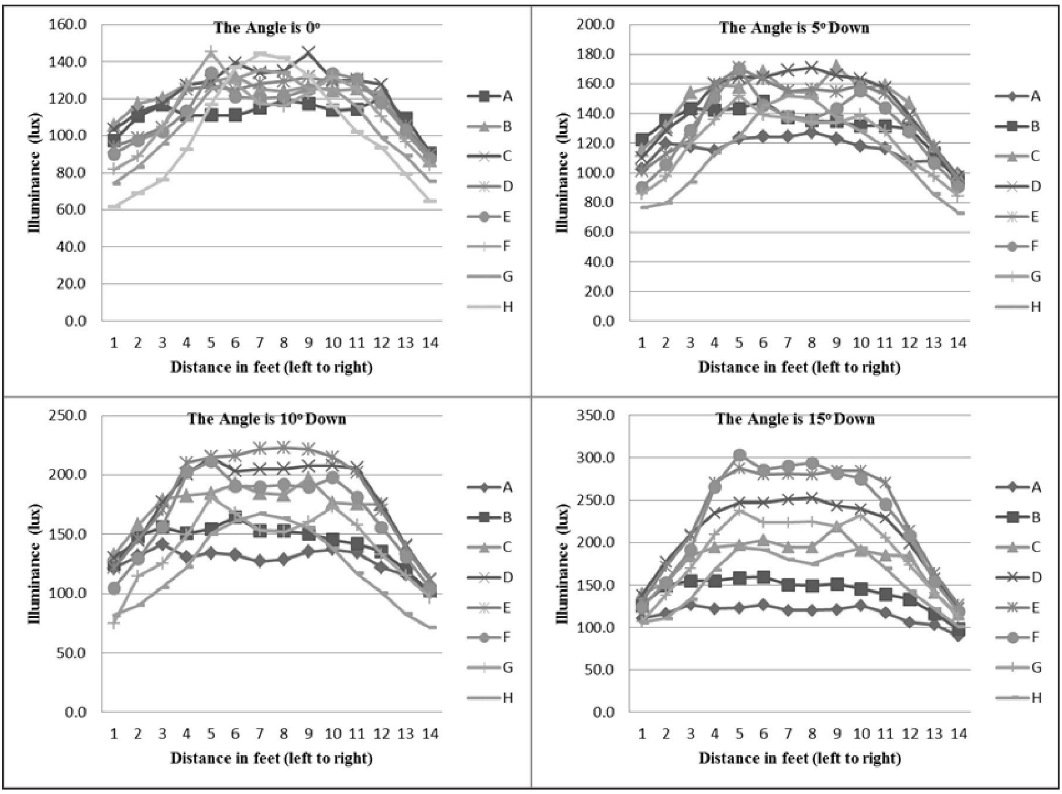
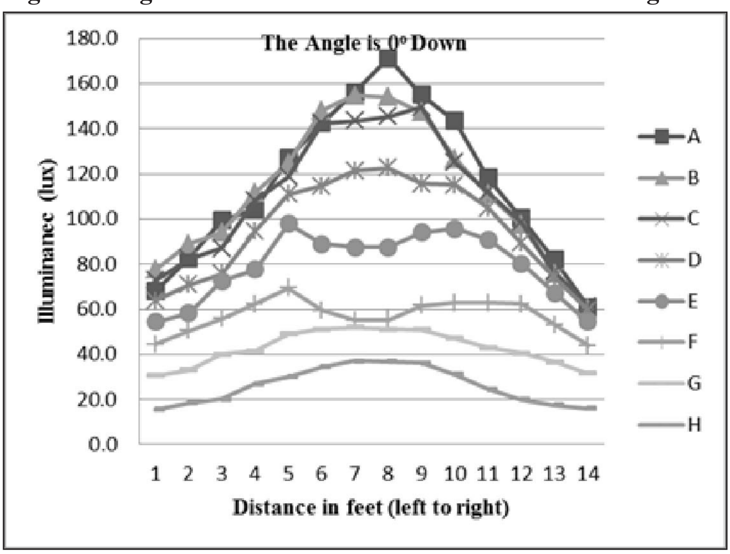


Figure 6: Light Distribution of the 62 Watt LED at 0° Angle



Comparison of Optimum Light Distributions of Five Light Sources

To determine which light source was most advantageous to illuminate overhead guide signs, the optimum light distribution at each row of the white sheet of paper was compared for the five light sources. Figure 7 shows light distribution at each row on the sheet of paper (A to H) for the sources. Again, row "A" is 8 ft. in height from the light source top surface, and row "H" is 1 ft. in height.

For each row, the 250 watt HPS light source provided highest illuminance values, meaning that it provides overhead guide signs with highest illuminance. The 250 watt MH light source provided the next highest illuminance values, followed by the 85 watt induction lighting, the 250 watt MV, and the 62 watt LED. However, higher illuminance does not mean better visibility. At some point, the visual performance reaches a plateau as a function of light level, and higher levels of light do not meaningfully increase visibility. Based on the previous fact, we excluded both the 250 watt HPS and the 250 watt MH since they produced high illuminance values. The MV is no longer available in the U.S. market because of the EISA of 2007; however, some other countries still use this source. As a result, the 85 watt induction provided the average illuminance values and it could be the best light source to increase visibility and safety.

LIGHT SOURCES COST ANALYSIS

Various companies were contacted to ask the prices and the costs associated with the 250 watt MH, 250 watt MV, 250 watt HPS, 85 watt induction, and 62 watt LED light sources studied for light distribution. Four companies provided information regarding the cost and lifespan of the five light sources studied in 2013. Cost calculations were based on light source use for an average of 11 hours per night (average daily operating hours), and the price of electricity was assumed to be \$0.08 per kWh. The selection of 11 hours as an average daily operating hours was an approximation from researchers who performed this study, and the selection of the electricity price to be \$0.08 per kWh was suggested by a KDOT engineer in charge of signage lighting. Labor and equipment costs were not included. Replacing ballast was not included in calculations since adding it will not affect comparison.

In this section, a detailed comparison between the five light sources is presented. A 50-year comparison period was selected for cost comparison in order to include maintenance factors for the light sources over time. Cost analysis shown in Table 3 includes initial, operating, and maintenance cost components of each light source. Data of initial light source cost and lifespan in hours for each source were obtained from the manufacturers.

Figure 7. Comparison of Optimum Light Distribution at Each Row on the White Paper

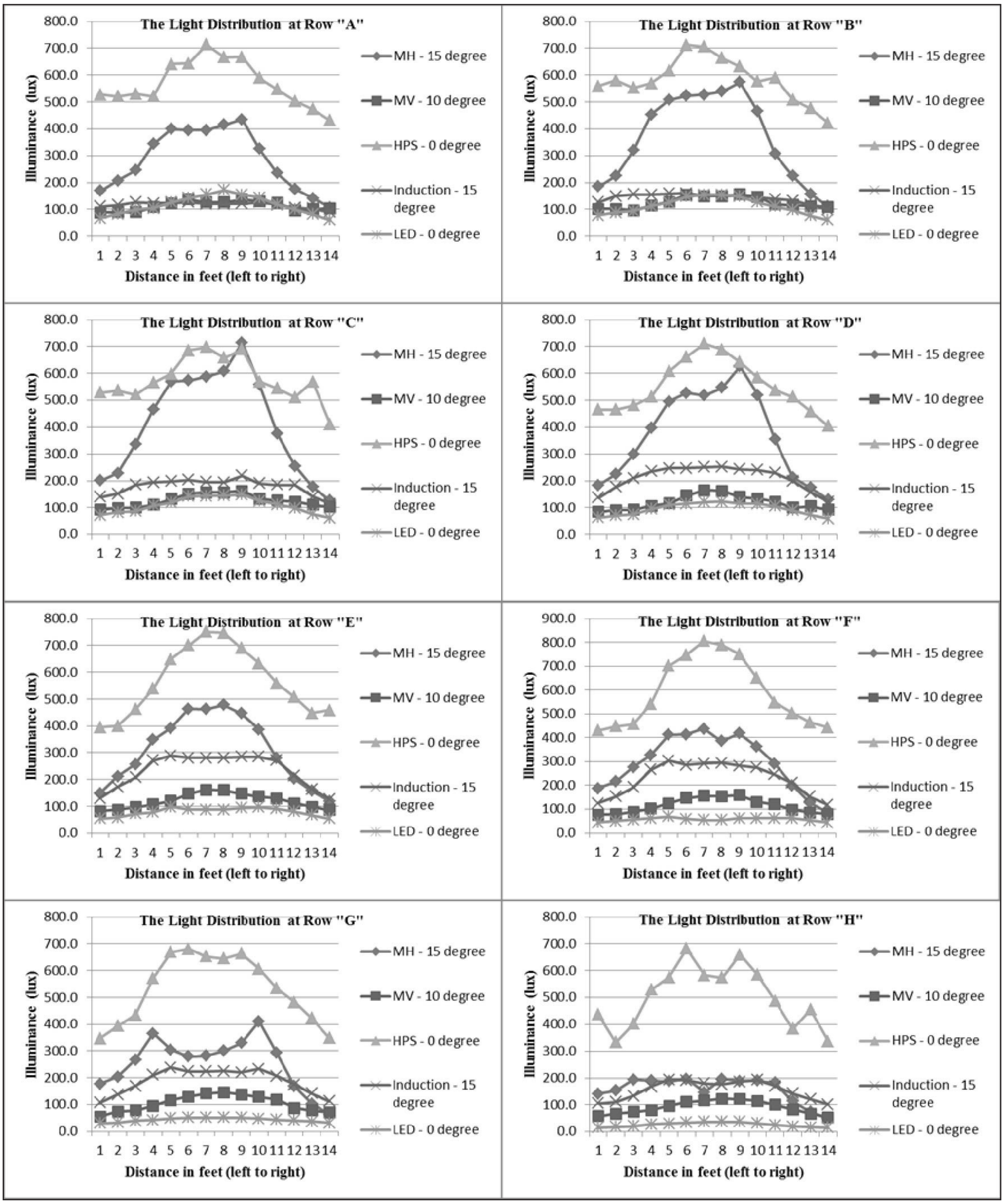


Table 3: Light Sources Cost Comparison

	Details	62 watt LED	85 watt induction	250 watt MH	250 watt HPS	250 watt MV
1	Initial cost ($)	600	678.3	678.3	678.3	678.3
2	Life (hours)	50,000	50,000	30,000	30,000	30,000
3	Life (years)	≅ 12.5	≅ 12.5	≅ 7.5	≅ 7.5	≅ 7.5
4	Daily power consumption (kW)	0.682	0.935	2.75	2.75	2.75
5	Annual power consumption (kW/year)	248.93	341.3	1,003.75	1,003.75	1,003.75
6	Life power consumption (kW)	3,100	4,250	7,500	7,500	7,500
7	Number of maintenance in 50 years	3	3	5.67	5.67	5.67
8	Total power consumption (kW/50 years)	12,446.5	17,065	50,187.5	50,187.5	50,187.5
9	Maintenance required	Replace unit	Replace lamp	Replace lamp	Replace lamp	Replace lamp
10	Maintenance cost ($/each time required)	600	75	30	16	25
11	Total maintenance cost ($/50 years)	1,800	225	170.1	90.72	141.75
12	Daily operating cost ($)	0.05456	0.0748	0.22	0.22	0.22
13	Annual operating cost ($)	19.914	27.302	80.30	80.30	80.30
14	Life operating cost ($)	248	340	600	600	600
15	Total operating cost ($/50 years)	995.7	1,365.1	4,015	4,015	4,015
16	Total cost ($/50 years)	3,395.7	2,268.4	4,863.4	4,784.02	4,835.05
17	Average annual cost ($)	67.91	45.37	97.27	95.68	96.70

For calculations in Table 3, life in years was calculated by dividing the light source life in hours by average daily operating hours (11 hours) and then dividing by 365 (days per year). For example, the 62 watt LED life is approximately 12.5 years (50,000 hours/ [11 hours per day × 365 days per year]). Daily power consumption was calculated by multiplying wattage consumed per hour for each light source by daily operating hours. For example, daily power consumption for the 62 watt LED is 0.682 kW (0.062 kW × 11 hours). Annual power consumption was calculated by multiplying daily power consumption by 365 (days per year). For example, yearly power consumption for the 62 watt LED is 248.93 kW (0.682 kW × 365 days). Life power consumption was calculated by multiplying yearly power consumption for each light source by its life in hours, dividing by average operating hours per day, and then dividing by 365 days per year. For example, power consumption during the life of the 62 watt LED is 3,100 kW (248.93 kW × 50,000 hours / [11 hours × 365 days]).

The amount of required maintenance during a 50-year period was calculated by dividing the 50-year period by the lifespan in years for each light source and subtracting one. One was subtracted because the assumption was made that at the time of installation, no maintenance is required and the light source was ready for use. For example, for the 62 watt LED during the 50-year period, three times the maintenance is required ([50 years/12.5 years]-1). Required maintenance is different based on light source type. For the 62 watt LED, required maintenance means replacing the entire light source fixture. For other light source types, however, lamp replacement is the primary required maintenance along with replacing ballast. LED maintenance cost is equal to the initial installation cost with the assumption that the cost remains constant over time. For example, three maintenance times are required for the 62 watt LED during 50 years, for a total maintenance cost of $1,800 (3 times × $600).

Total power consumption in 50 years was calculated by multiplying power consumption per year times 50. For example, power consumption for the 62 watt LED per 50 years is 12,446.5 kW (248.93 kW × 50 years). Daily operating cost was calculated by multiplying daily power consumption for each light source by the electricity price ($0.08 per kWh). For example, for the 62 watt LED, daily operating cost is $0.05456 (0.682 kW × $0.08). Annual operating cost was calculated by multiplying daily operating cost by 365 days per year. For example, for the 62 watt LED, annual operating cost is $19.914 ($0.05456 × 365 days). Life operating cost was calculated by multiplying annual operating cost by the light source's lifespan in hours, dividing by daily operating hours, and then dividing by 365 days per year. For example, life operating cost for the 62 watt LED is $248 ($19.914 × 50,000 hours/ [11 hours × 365 days]).

The total cost for each light source over 50 years was calculated by adding the initial cost of the light source, operating cost over 50 years, and maintenance cost over 50 years. For example, total cost for the 62 watt LED is $3,395.7 ($600 + $995.7+ $1,800). The average annual cost of a light source was calculated by dividing the total cost during 50 years by 50. For example, the average annual cost for the 62 watt LED is $67.91 ($3,395.7/50 years).

Based on the average annual cost of each light source as shown in Table 3, the 85 watt induction light was found to be the most cost-effective light source, followed by the 62 watt LED, 250 watt HPS, 250 watt MV, and 250 watt MH.

Based on annual power consumption for each light source, the 62 watt LED was found to be most effective for power consumption because it consumes the least amount of power, and the induction lighting was the next in energy consumption. In regards to environmental issues related to the presence of toxic materials in the light source, all light sources except the LED contained some amounts of lead or mercury or both, except for the 62 watt LED used in this experiment, which was the friendliest to the environment. In addition, the 62 watt LED has the minimum power consumption, which itself is a benefit to the environment.

CONCLUSIONS

Five light sources were compared to determine the optimal light source to illuminate overhead guide signs, consequently increasing their visibility and safety. These light sources were the 250 watt MH, 250 watt MV, 250 watt HPS, 85 watt induction, and 62 watt LED. Various decision criteria, including light distribution, average annual cost, and environmental issues, were considered in order to compare light sources.

According to the light distribution experiment, the 250 watt HPS light source had the highest illuminance readings, followed by the 250 watt MH, 85 watt induction lighting, 250 watt MV, and 62 watt LED. Based on the fact that higher illuminance does not mean better visibility, both the 250 watt HPS and the 250 watt MH produced high illuminance values on the sign, which led us to conclude that both of them might not increase visibility. The MV is no longer available in the U.S. market because of the EISA of 2007 law. Based on the light distribution criterion, the 85 watt induction, which provided the average illuminance values, could be the best light source to increase visibility and safety.

Considering the cost analysis for the five light sources, the 85 watt induction light source is the most cost effective because it had minimum average annual cost, followed by the 62 watt LED. Considering environmental issues that are related to the presence of mercury in the light source and electric power consumption, the 62 watt LED was the most environmentally friendly light source because it is free of mercury and consumed the minimum electric power, thereby saving a large amount of electric energy.

Overall, merging the result of the light distribution experiment with the cost analysis, the induction lighting could be the most cost-effective light source that provides sufficient illuminance on the sign and contributes to better sign visibility to the driver, and consequently higher safety. For those agencies that prefer using sources that are friendlier to the environment, the LED could be a good choice.

Acknowledgements

The authors wish to express their appreciation to Kansas Department of Transportation (KDOT) for funding this project through a grant to Kansas State University. In addition, the authors gratefully acknowledge the support and generosity of KDOT and Lumi Trak Company for providing the light sources used in this research. Finally, the authors wish to express many thanks to Mr. Timothy Deines for his support while performing the experiment.

References

Amparano, G., and D. Morena. Senior Mobility Series: Article 4- Marking the Way to Greater Safety. U.S. Department of Transportation, Federal Highway Administration, Washington, DC, 2006.

Avrenli, K., R. Benekohal, and J. Medina. LED Roadway Lighting Volume 1: Background Information. Illinois Center for Transportation, Bureau of Materials and Physical Research, Springfield, IL, 2012.

BITS. How Long Did You Say That Bulb Would Last? 2012.

http://bits.blogs.nytimes.com/2009/02/11/how-long-did-you-say-that-bulb-will-last/ (accessed May 15, 2012).

Bullough, J. Guide for Optimizing the Effectiveness and Efficiency of Roadway Lighting. The Lighting Research Center, Rensselar Polytechnic Institute, Troy, NY, 2012a.

Bullough, J. New Lighting Technologies and Roadway Lighting: An Informational Brochure. Lighting Research Center at Rensselaer Polytechnic Institute, Troy, NY, 2012b.

Bullough, J., N. Skinner, and C. O'Rourke. Evaluation of New Reflective Materials for Overhead Highway Signage. Lighting Research Center at Rensselaer Polytechnic Institute, Troy, NY, 2008.

California Department of Toxic Substances Control. Restrictions on the Use of Certain Hazardous Substances in General Purpose Lights, 2010.

https://dtsc.ca.gov/HazardousWaste/UniversalWaste/RoHS_Lighting.cfm (accessed June 23, 2014).

Deco Lighting. Induction Lighting, 2010. http://www.getdeco.com/induction/ (accessed May 12, 2012).

Dewar, R., and P. Olson. *Human Factors in Traffic Safety. 2 ed.* Lawyers and Judges Pulishing Company Inc., Tucson, AZ, 2007.

Dukic, T., and T. Broberg. "Older Drivers' Visual Search Behaviour at Intersections." *Transportation Research Part F: Traffic Psychology and Behaviour* 15(4), (2012): 462-470.

FHWA. New Sign Retroreflectivity Requirements. The U.S. Department of Transportation, Federal Highway Administration, Washington, DC, 2008.

FHWA. Manual on Uniform Traffic Control Devices for Streets and Highways. The U.S. Department of Transportation, Federal Highway Administration, Washington, DC, 2009.

GRAH Lighting. Street Lighting Technology Comparison, 2014.
http://www.grahlighting.eu/learning-centre/street-lighting-technology-comparison (accessed June 23, 2014).

Lagergren, E. Traffic Sign Retroreflectivity Measurement Using Human Observers. Washigton State Department of Transportation, Olympia, WA, 1987.

Lim, S., D. Kang, O. Ogunseitan, and J. Schoenung. "Potential Environmental Impacts of Light-Emitting Diodes (LEDs): Metallic Resources, Toxicity, and Hazardous Waste Classification." *Environmental Science & Technology* 45, (2010): 320-327.

Lopez, C. Highway Illumination Manual. Texas Department of Transportation, Traffic Operations Division, Austin, TX, 2003.

Medina, J., K. Avrenli, and R. Benekohal. "Field and Software Evaluation of Illuminance from LED Luminaires for Roadway Application." *Transportation Research Board*, Washington, DC, 2013.

NHTSA. "Traffic Safety Facts: 2013 Motor Vehicle Crashes: Overview." The U.S. Department of Transportation, National Highway Traffic Safety Administration, NHTSA's National Center for Statistics and Analysis. Washington, DC, 2014.

Obeidat, M.S., J.R. Malgorzata, E. Russell, and A. Gund. "Determining Cost-Effective Policy for Visibility of Overhead Guide Signs on Highways." *Journal of the Transportation Research Forum* 53(2), (2014): 45-58.

Obeidat, M.S., J.R. Malgorzata, and E. Russell. Overhead Guide Sign Retroreflectivity and Illumination. Kansas Department of Transportation, Topeka, KS, 2015.

Recycle SD Inc. Recycling Low and High Pressure Sodium Lamps. 2014.
http://recyclesandiego.org/recycling-item/low-high-pressure-sodium-lamps/ (accessed June 23, 2014)

Tri-State LED, 2012. http://www.ledlightingwholesale.com/c/69/energy-efficient-led-street-lights-cobrahead-roadway-lamps (accessed May 4, 2012).

Mohammed Said Obeidat *is an assistant professor in the Department of Industrial Engineering at Jordan University of Science and Technology. He obtained his B.S. (2004) and M.S. (2008) degrees from Jordan University of Science and Technology, Irbid, Jordan, and Ph.D. from Kansas State University; all in industrial engineering.*

Margaret J. Rys *is an associate professor in the Department of Industrial and Manufacturing Systems Engineering at Kansas State University. She obtained her integrated B.S./M.S. degree from the Technical University of Wroclaw, Poland, in 1979 and M.S. (1986) and Ph.D. (1989) from Kansas State University; all in industrial engineering. She has over 20 years of experience conducting research and teaching courses in human factors engineering, quality, engineering economy, statistics, and safety. During the past 20 years she has been principal or co-principal investigator on more than 40 projects and authored and co-authored more than 50 journal papers.*

Book Review

Todorovich, Petra, Schned, Daniel, and Lane, Robert. High-Speed Rail: International Lessons for U.S. Policy Makers. *Policy Focus Reports. Cambridge, Mass.: Lincoln Institute of Land Policy, 2011. 60 pp. ISBN 978-1-55844-222-1.*

High Speed Rail: International Lessons for U.S. Policy Makers

by Melvin A. Sacks

The authors of *High Speed Rail*, Petra Todorovich, Daniel Schned, and Robert Lane, state that over the past 50 years U.S. transportation spending has favored interstate highway and aviation systems. In contrast, China, Japan, Spain, France and Germany have been working on modern high-speed rail (HSR) systems. In the United States, HSR construction has been stalled because of a lack of additional appropriations from Congress. A high-speed line in California is still on track to be completed, though with relatively modest federal funding.

The authors divide the book into several parts: international experience with HSR, the potential benefits of HSR, U.S. policy and programs for HSR, and HSR progress in California and the Northeast corridor.

HSR in cities in Europe, China, and Japan attract commercial development and urban regeneration. It offers greater operating energy efficiency than competing modes and takes up less land than highways. The authors state that an HSR line could create similar transportation, economic, environmental, and safety benefits in America if only there was sufficient funding.

Since the 1964 inauguration of Japan's first Shinkansen bullet train connecting Tokyo to Osaka, commercial HSR has been constructed in 14 countries, generating billions of passenger trips. It saves many hours in travel time, is reliable, rapid and safe, increases regional mobility and accessibility, saves energy by reduced fuel use, regenerates cities and regions, and increases economic productivity.

The United States failed to develop HSR and fully realize its benefits despite numerous planning studies and aborted attempts to expand rail service in various regions since 1960. Americans are therefore unfamiliar with HSR and its potential benefits. Aviation and highways have been funded in the tens of billions of dollars, but not so passenger rail. Such funding has been a precondition to bringing large rail capital projects to fruition in other countries. The authors could have developed a detailed discussion of how the U.S. political process and its divergent ideologies, especially with parsimonious congressional appropriations, prevent meaningful infrastructure improvements, particularly in regard to rail projects, presently and in the near future. However, the authors do well in pointing out the divergence between advanced countries with developed HSR systems and the United States, currently without a true HSR network.

At least 19 countries around the world are building or planning new HSR lines. China has invested several hundred billion dollars in building the world's most extensive HSR system. In Saudi Arabia, Haramain's high-speed line will operate on the 280-mile line from Mecca to Jeddah.

In the United States, President Barack Obama, in his 2012 budget, proposed $53 billion over the following six years to begin developing a national high-speed and connected passenger rail network that could connect 80% of Americans. Congress rejected the proposal, calling it wasteful and not true high-speed technology. In light of the opposition, proponents need to lay out a compelling case for its benefits for any possibility legislative success.

High-speed trains with an advanced signaling system can operate with greater frequency, creating greater capacity to move passengers. In 2011, 11 countries directly operated high-speed trains at speeds up to 185 mph and several can reach 215 mph, the current international standard. High speed trains often travel in dedicated high-speed tracks.

Two of the most notable HSR technologies introduced are tilting mechanisms to counteract physical forces around curves and magnetic levitation trains, without tilting mechanisms but requiring installation of new dedicated high-speed tracks.

GENESIS AND TRACK RECORD

The high-speed Tokyo line in Japan has carried more than five billion passengers and is the world's busiest HSR line.

The authors point out that HSR did not come right away, and it was not until 1981 that France introduced the TGV, Europe's first high-speed line connecting Paris with Lyon. It reduces travel time to two hours for the 280-mile journey. In the 1980s Germany, Belgium, and Spain converted to HSR lines. Since 2000 HSR lines have been introduced in England, South Korea, Switzerland, Taiwan, Netherlands, and Turkey. China opened its first HSR line in 2003 and shortly after built the world's most extensive HSR network with well over 5,000 miles of HSR.

This long experience with HSR in other countries gives them an advantage in design, manufacturing, and safety issues compared with the United States. Also, government is largely involved in the development and operation of HSR overseas, and the authors could have noted the hostility to government in many quarters in the United States that views government funding of significant infrastructure projects unfavorably. In the United States, only the Acela is somewhat high speed and briefly reaches 150 miles per hour but averages only 75 miles per hour. Infrastructure along the Northeast Corridor seriously needs upgrading. For example, the Baltimore tunnel built in 1873, currently used by Acela and regional and commuter trains, limits speeds on the Northeast Corridor to 30 mph due to a sharp turn and steep grade. Outside the Northeast Corridor, trains are owned by freight railroads, and this restricts the ability to develop passenger rail speed frequency and reliability. U.S. administrations and congresses tried to develop selected HSR corridors in a program called high-speed Intercity Passenger Rail, but Congress wasn't allocating a competitive grant program of sufficient funding.

California's HSR was initially awarded a federal grant designed to be a core express service with top speeds of 220 miles per hour on new dedicated tracks. Since the train going at 200 miles per hour requires 16 miles of straight track and also need significant distances to break and come to a stop, stations must be well spaced along HSR corridors.

ECONOMIC BENEFITS

The authors note that after 50 years of international experience HSR has proven it is capable of producing a wide range of transportation, economic, and environmental benefits:

- Shortened travel time, especially between urban centers. It improves overall access to many destinations. It captures over 80% of air for rail trips if a high-speed train trip is less than two and a half hours.
- Excellent safety records.
- Better on-time performance than cars or airplanes.
- Efficiencies: the typical HSR line has the ability to transport the same number of people in the same direction as a three-lane highway but on a fraction of the land area.

HSR's ability to promote economic growth is grounded on its capacity to increase access to markets. Economic development is more likely to occur in places with more and better transportation infrastructure. HSR increases productivity, employment, and wages.

HSR stations attract new tourist and business travelers who might not have made the trip otherwise. A study by the U.S. Conference of Mayors in 2010 concluded that building HSR would increase spending annually by about $225 million in the Orlando region, $360 million in Metropolitan Los Angeles, $15 million in the Chicago area, and $100 million in Greater Albany, New York.

HSR creates thousands of construction-related jobs in design, engineering, planning, and construction, as well as maintenance and operations. In China, over 100,000 construction workers have been involved in building the HSR line that connects Beijing and Shanghai. Sustained investment could foster the development of new manufacturing industries for rail cars and other equipment, and generate large amounts of related employment. HSR can rejuvenate neighborhoods around HSR stations. HSR can generate growth in real estate markets and anchor investment in commercial and residential developments around train stations.

ENVIRONMENTAL BENEFITS

HSR offers greater operating efficiencies on a per-passenger-mile basis than competing modes, such as single occupancy automobiles, or airplanes that require significant amounts of fuel to get off the ground. Japanese trains are estimated to use one-quarter of the energy of airplanes and one-sixth of private automobiles per passenger mile. But high-speed trains must maximize load factors to realize greater efficiencies.

Attracting passengers to HSR can reduce overall energy usage. HSR is the only available mode of long-distance travel that is not currently dependent on motor fuels. However, it is powered by electricity, which is often generated by fossil fuels. A new HSR line in the Northeast Corridor, powered by electricity from the current energy mix, would shift 30 million riders from cars and planes to rails, attract six million new riders, and still reduce car emissions of carbon monoxide by more than three million tons annually. Here the authors could have more solidly tied the need to reduce emissions to the urgent need of reducing carbon dioxide, which increases global warming.

TECHNOLOGICAL INNOVATIONS

Innovation is needed in HSR. Since more energy is devoted to higher speeds, designing trains to be lighter in weight and more aerodynamic would require greater innovation, especially for crash worthiness. This presents a challenge to U.S. HSR. In addition, crash avoidance systems require innovation in advanced signaling systems.

U.S. POLICY

The initial commitment to high-speed rail began in 2008 when Congress passed the Passenger Rail Investment Procurement Act (PRIIA), which authorized funds for Amtrak and the states to develop HSR corridors between 2009 and 2013. Appropriations totaling $10.5 billion for high-speed and passenger rail became the centerpiece of the Obama Administration in its infrastructure agenda. However, the subsequent Congressional appropriation for FY 2011 stripped the passenger program of any funding in 2011 and rescinded $400 million from the FY 2010 budget. That put the brakes on HSR.

CALIFORNIA AND NORTHEAST CORRIDOR

California's 2009 population of 37 million people is expected to grow by 25 million by 2050. The Northeast will add an additional 12 million people by 2050. Major highways and airports are reaching capacity and HSR is badly needed to move people around. California would need to add

3,000 highway lane miles and five new airports at twice the cost if HSR is not available. Otherwise California will experience very high congestion on its highways.

Upon completion of HSR, the California system will operate trains at speeds up to 220 miles per hour, reducing the travel time to two hours 40 minutes for the 432-mile trip from Los Angeles to San Francisco. The cost is at least $43 billion and its funding includes public-private partnerships. Developing the first segment of the Initial Operating Section from Madera to Bakersfield will cost $6 billion, consisting of $3.3 billion in federal funding and $2.6 billion in Proposition 1A bond proceeds. It is the largest HSR project in the United States and a success or failure would signal whether future HSR lines in the country will be built. But opposition has grown as the expense of HSR in California has impinged on other budget priorities. Local communities are also voicing opposition. Defunding of PRIIA has raised doubts about continued federal participation in the HSR program.

The 450-mile Northeast Corridor (NEC) between Boston and Washington is America's most intensely used rail line and one of the most heavily traveled corridor in the world, accounting for approximately 13 million annual passengers. Since November 2009 Amtrak has experienced 20 consecutive years of ridership growth. Amtrak predicts that by 2050 ridership will grow 59%. But roadblocks for HSR include outmoded tracks, bridges, power, and communication systems on many stretches that need to be upgraded. Amtrak needs $8.8 billion to achieve a state of good repair in a congressional environment of cost-cutting. This is in addition to $43.5 billion to expand the corridor's capacity and reliability. Amtrak introduced Acela Express for highest speed rail service in December 2000, but has struggled to obtain enough funding for basic maintenance, capital investments, or funding to improve reliability. Lacking a dedicated track network, Acela trains mostly operate in congested tracks that also carry northeast regional service and assorted commuter rail lines, resulting in much lower rates of on-time performance and frequency compared with HSR systems around the world. Acela trains average only 62 miles per hour between New York and Boston. Economic mobility benefits would be enhanced if a dedicated HSR right-of-way could be built. But the cost would be over $117 billion. The $27 trillion economy in the Northeast is known for its high population density and its growing congestion of existing rail, roads, and runways, making a strong case for this HSR investment. But without federal support, national and regional HSR projects are unlikely to secure a necessary state or private funding commitments needed to proceed.

In summary, the authors did a good job of presenting the international experience with HSR, the benefits, and the lack of progress for HSR in the United States. The authors could have made even a stronger case for the congestion and consequent harm to the economy if an efficient means of moving people, most notably high-speed rail, does not proceed in the United States.

***Melvyn A. Sacks** is the Maryland representative on the Council of the National Association of Railroad Passengers, and is currently president of the Transportation Research Forum-Washington Chapter. He did an in-depth study of world railroad locomotives at the Export-Import Bank of the United States. Sacks experienced travel on European and Asian passenger trains ranging from Vietnam to Spain and Russia. He also traveled extensively on U.S. passenger trains prior to Amtrak.*

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.

TRF Council

TRF Foundation Officers

Past Presidents

2015	David Ripplinger
2014	Art Guzzetti
2013	Jack Ventura
2012	Ken Button
2011	Alan R. Bender
2010	B. Starr McMullen
2009	Richard Gritta
2008	Kenneth Button
2007	John (Jack) V. Wells
2006	Anthony M. Pagano
2005	Scott E. Tarry
2004	John S. Strong
2003	C. Gregory Bereskin
2002	Martin Dresner
2001	Mark R. Dayton
2000	Richard S. Golaszewski
1999	Aaron J. Gellman
1998	Richard Beilock
1997	Robert Harrison
1996	Clinton V. Oster, Jr.
1995	Paul K. Gessner
1994	Russell B. Capelle, Jr.
1993	Louis A. LeBlanc
1992	Stephen J. Thompson
1991	Joanne F. Casey
1990	Frederick J. Beier
1989	Thomas N. Harvey
1988	Joedy W. Cambridge
1987	Frederick C. Dunbar
1986	Carl D. Martland
1985	Allan D. Schuster
1984	Douglas McKelvey
1983	William B. Tye
1982	Michael S. Bronzini
1981	Jay A. Smith, Jr.
1980	Samual E. Eastman
1979	Lana R. Batts
1978	Carl J. Liba
1977	Gerald Kraft
1976	Edward Morlok
1975	Barry A. Brune
1974	Richard Shackson
1973	Harvey M. Romoff
1972	Arthur Todd
1971	Herbert E. Bixler
1970	Paul H. Banner
1969	George W. Wilson
1968	Donald P. MacKinnon
1967	David L. Glickman
1966	Edward Margolin
1965	Robert A. Bandeen
1964	Gayton Germane
1963	Herbert O. Whitten
1962	Herbert O. Whitten
1961	Herbert O. Whitten
1960	Herbert O. Whitten
1959	John Ingram (TRF of NY)
1958	Herbert O. Whitten (TRF of NY)

Recipients of the TRF Distinguished Transportation Researcher Award

2016	Robin Lindsey
2015	Allen D. Biehler
2014	Joseph M. Sussman
2013	Wayne K. Talley
2012	Genevieve Giuliano
2011	Martin Wachs
2010	Clifford Winston
2009	Daniel McFadden
2008	Steven A. Morrison
2007	José A. Gomez-Ibanez
2006	Tae H. Oum
2005	Kenneth Button
2004	Kenneth Small
2000	Michael E. Levine
1998	Edward K. Morlok
1997	Carl D. Martland
1996	Benjamin J. Allen
1995	D. Philip Locklin
1994	Martin T. Farris
1993	C. Phillip Baumel
1992	Alan A. Altshuler
1990	George W. Wilson, Ph.D.
1989	Sir Alan Arthur Walters, B. Sci., Hon. D. Soc. Sci.
1988	Karl M. Ruppenthal, Ph.D.
1987	William S. Vickrey, Ph.D.
1986	William J. Harris, D. Sci., Hon. D. Eng.
1985	John R. Meyer, Ph.D.
1984	Alfred E. Kahn, Ph.D.
1982	W. Edwards Deming, Ph.D.
1979	James C. Nelson, Ph.D.
1978	James R. Nelson, Ph.D.
1977	Lewis K. Sillcox, D. Sci., D. Eng., LL.D., D.H.L.

Recipients of the Herbert O. Whitten TRF Service Award

2016	Wayne Talley
2015	Ian Savage
2014	Kenneth Button
2013	B. Starr McMullen
2012	Kofi Obeng
2011	Anthony Pagano
2010	Captain James R. Carman
2009	John (Jack) Wells
2008	Gordon MacDougall
2007	Robert T. Beard
2006	Gene C. Griffin
2005	Michael W. Babcock
2004	Jack S. Ventura
2000	Paul K. Gessner
1998	Arthur W. Todd
1996	Stephen J. Thompson
1994	Samuel Ewer Eastman
1991	Carl D. Martland, C.E.
1990	Herbert O. Whitten, M.B.A.

Past Editors of JTRF

Kofi Obeng (2005-2014)
Wayne K. Talley (1998-2000)
K. Eric Wolfe (1993-1998)
Kevin H. Horn (1993-1998)
Anthony M. Pagano (1987-1993)
Richard Beilock (1987-1993)

Recipients of the TRF Best Paper Award

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

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

2015 Chen (Sarah) Xu and Liang-Chieh (Victor) Cheng, *Accounting for Natural Gas Vehicles in Regional Auto Markets–Estimates for the State of Texas, U.S.*

2014 Ju Dong Park and Won W. Koo, *The Magnitudes of Economic and Non-Economic Factors in Demand for U.S. Domestic Air Passengers*

2013 Carl Martland, *Introduction of Heavy Axle Loads by the North American Rail Industry, 1990 to 2012*

2012 Rafael Costa & C. Parr Rosson, III, *The Impacts of the Panama Canal Expansion on World Cotton Trade*

2011 Alexander Bigazzi and Miguel Figliozzi, *A Model and Case Study of the Impacts of Stochastic Capacity on Freeway Traffic Flow and Benefits Costs*

2010 Tony Diana, *Predicting Arrival Delays: An Application of Spatial Analysis*

2009 Tae H. Oum, Jia Yan, and Chunyan Yu, *Ownership Forms Matter for Airport Efficiency: A Stochastic Frontier Investigation of Worldwide Airports*

2008 C. Gregory Bereskin, *Railroad Cost Curves Over Thirty Years – What Can They Tell Us?*

2007 Rob Konings, Ben-Jaap Pielage, Johan Visser, Bart Wiegmans, *"Container Ports and Their Hinterland: Multimodal Access and Satellite Terminals within the Extended Gateway Concept"*

2006 Ian Savage, *Trespassing on the Railroad.*

2005 Patrick DeCorla-Souza, *A New Public-Private Partnership Model for Road Pricing Implementation.*

2004 Ian Savage and Shannon Mok, *Why Has Safety Improved at Rail-Highway Crossings*?

2000 Ian Savage, *Management Objectives and the Causes of Mass Transportation.*

1999 C. Phillip Baumel, Jean-Philippe Gervais, Marty J. McVey, and Takehiro Misawa*, Evaluating the Logistics Economic Impacts of Extending Six Hundred Foot Locks on the Upper Mississippi River: A Linear Programming Approach*.

1998 Carl Scheraga and Patricia M. Poli, *Assessing the Relative Efficiency and Quality of Motor Carrier Maintenance Strategies: An Application of Data Entry Envelopment Analysis*.

1997 Wayne K. Talley and Ann Schwarz-Miller, *Motor Bus Deregulation and Racial/Gender Effects: Earnings and Employment*.

1996 Todd Litman, *Full Cost Accounting for Transportation Decision Making: Estimates, Implications and Applications*.

1995 Leon N. Moses and Ian Savage, *A Cost-Benefit Analysis of United States Motor Carrier Safety Programs*.

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

1993 W. Bruce Allen and Dong Liu, *Service Quality and Motor Carrier Costs: An Empirical Analysis*.

1992 Victor E. Eusebio, Stephen J. Rindom, Ali Abderrezak, and John Jay Rosacker, *Rail Branch Lines at Risk: An Application of the Exponential Survival Model on Kansas Duration Data*.

1991 Patrick Little, Joseph M. Sussman, and Carl Martland, *Alternative Freight Car Maintenance Policies with Attractive Reliability/Cost Relationships*.

1990 James A. Kling, Curtis M. Grimm, and Thomas M. Corsi, *Strategies of Challenging Airlines at Hub-Dominated Airports*.

1989 Cathy A. Hamlett, Sherry Brennan, and C. Phillip Baumel, *Local Rural Roads: A Policy Analysis*.

1988 John R. Brander, B. A. Cook, and John Rowcroft, *Auctioning Runway Slots: Long Term Implications.*

1987 Clinton V. Oster, Jr. and C. Kurt Zorn, *Deregulation's Impact on Airline Safety.*

1986 Chulam Sarwar and Dale G. Anderson, *Impact of the Staggers Act on Variability and Uncertainty of Farm Product Prices*.

1985 Brian D. Adam and Dale G. Anderson, *Implications of the Staggers Rail Act of 1980 for Level and Variability of Country Elevator Bid Prices*.

Donald J. Harmatuck, *Back Haul Pricing: Mathematical Programming and Game Theory Approaches to Allocating Joint Costs*.

Jeffrey L. Jordan, Dieudonne Mann, S. E. Pressia, and C. Thai, *Managing the Transportation of Perishable Commodities: Temperature Control and Stacking Patterns*.

1984 K. Eric Wolfe, *An Examination of Risk Costs Associated with the Movement of Hazardous Materials*.

1983 Denver D. Tolliver, *Economics of Density in Railroad Cost-Finding: Applications to Rail Form A*.

1982 Jeffrey Beaulieu, Robert J. Hauser, and C. Phillip Baumel, *Inland Waterway User Taxes: Their Impacts on Corn, Wheat and Soybean Flows and Transport Costs*.

Journal of the Transportation Research Forum Guidelines for Manuscript Submission

1. Submit manuscripts by e-mail or hardcopy to either General Editor at:

Michael W. Babcock
Co-General Editor, JTRF
Department of Economics
Kansas State University
Manhattan, KS 66506 U.S.A.
Phone: (785) 532-4571
Fax: (785) 532-6919
Email: mwb@ksu.edu

James Nolan
Co-General Editor, JTRF
Dept. of Bioresource Policy, Business and Economics
University of Saskatchewan
Saskatoon, SK S7N 5A8 CANADA
Phone: (306) 966-8412
Email: james.nolan@usask.ca

2. E-mail submissions must be in MS WORD.

3. Final manuscript and abstract (hard or e-mail copy) must be received as soon as possible.

4. The text of manuscripts is to be double-spaced. Use one side of each page only. Articles are limited to a maximum length of 30 pages; industry issue papers and comments are limited to a maximum of 15 pages.

5. The manuscript should have a title page which includes the names, affiliations, address (mailing and e-mail) and phone numbers of all authors. Brief biographical sketches for all authors should be included with the manuscript.

6. The abstract should briefly describe the contents, procedures and results of the manuscript, not its motivation, and should not exceed 100 words.

7. Endnotes are to be used rather than footnotes, used sparingly and placed at the end of the manuscript. Do **NOT** use the endnote feature of the word processing software.

8. *The Chicago Manual of Style* is to be used for endnotes and references. At the end of the manuscript, complete references are listed alphabetically (not by number) by author surname, government agency, or association name. Use the following examples.

   Book:

   Jones, Robert T. *Improving Airline Transportation*. General Publishing Company, Washington, D.C., 2002.

   Chapter in a Book:

   Bresnahan, T.F. "Empirical Studies of Industries with Market Power." R. Schmalensee and R. Williq eds. *Handbook of Industrial Organization*. Amsterdam: North Holland (1989): 1011-1057.

   Journal Article:

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

   Journal Article with Multiple Authors:

   Chow, G., R. Gritta, and E. Leung. "A Multiple Discriminant Analysis Approach to Gauging Air Carrier Bankruptcy Propensities: The AIRSCORE Model." *Journal of the Transportation Research Forum* 31 (2), (1991): 371-377.

Ph.D Dissertation:

Jessup, E.L. "Transportation Optimization Marketing for Commodity Flow, Private Shipper Costs, and Highway Infrastructure, Impact Analysis." Dissertation (Ph.D). Washington State University, 1998.

Government Document:

U.S. Senate. Committee on Foreign Relations, *Investigations of Mexican Affairs*. 2 vols. 66th Cong., 2nd session, 1919-20.

9. Tables, figures, graphs, and charts should be titled and numbered by an Arabic numeral (e.g., Figure 2). All figures and charts should be submitted as **separate** files. Any graphics or photos must be 300 dpi and submitted as a separate .tif or .eps file.

10. Headings should adhere to the following style. Place the abstract below the title of the manuscript.

    • First level headings should be all caps, left justified.
    • Second level headings should be initial caps, left justified.
    • Third level headings should be initial caps on the same line as the first paragraph which it heads.
    • Do not number the headings.

11. Submit your final copy in "MS WORD" only.

12. For proper preparation of all charts, figures, maps and photos call Bev Trittin, North Dakota State University, at (701) 231-7137 or bev.trittin@ndsu.edu prior to submitting the final version of your paper. The journal is printed in black and white, therefore, all graphics must be submitted in black and white, or grayscale.

    TIPS:

    - Photographs to be submitted as individual files at 250 dpi or higher resolution (.jpg or .tif format).
    - Images taken from the web are 72 dpi and are not acceptable for print. Secure high resolution image when possible. Obtain permission for use of images taken from web.
    - Do not embed graphics in Word – submit as individual files (.jpg or .tif format).
    - If charts and figures are created in MS Excel, submit Excel file to Bev Trittin.
    - Improper graphics or images will be returned to author for correct formatting.

Book Review Information

Books for review should be mailed to:

Dr. Jack Ventura
Book Review Editor
1025 Chiswell Lane
Silver Spring, MD 20901
Phone: (301) 593-1872
Email: jack.ventura@verizon.net

JTRF Information

The Journal of the Transportation Research Forum is distributed to members of the Transportation Research Forum.

ISSN 1046-1469

The Transportation Research Forum gratefully acknowledges the contributions
of sustaining and supporting members.

2016 Supporting Members

Michael Babcock, Kansas State University
Paul Gessner, GTC LLC
Jack Ventura