JOURNAL of the TRANSPORTATION RESEARCH FORUM

Volume 53, Number 3 Fall 2014

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

Journal of the Transportation Research Forum

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ISSN 1046-1469

Published and Distributed by
Transportation Research Forum
NDSU Dept. 2880
P.O. Box 6050
Fargo, ND 58108-6050
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On the cover: Ju Dong Park and Won W. Koo identify the economic and non-economic factors that affect U.S. air travel in "The Magnitudes of Economic and Non-Economic Factors on the Demand for U.S. Domestic Air Travel." The authors find that airfare, income, seasonality, and mergers play significant roles in the demand for airline passenger travel.

BOOK REVIEWS

A Message from the JTRF Co-General Editors

The fall 2014 issue of JTRF contains articles covering a broad range of topics. They are:

- Optimizing Strategic Allocation of Vehicles for One-Way Car-sharing Systems Under Demand Uncertainty
- Measuring Performance at a Large Metropolitan Area: The Case of the DC (District of Columbia) Metroplex
- Determinants of Per Capita Vehicle Miles Traveled (VMT): The Case of California
- The Magnitudes of Economic and Non-Economic Factors in the Demand for U.S. Domestic Air Travel
- Forecast of C02 Emissions From the U.S. Transportation Sector: Estimation from a Double Exponential Smoothing Model
- State Variation in Railroad Wheat Rates
- Factors Contributing to Police Attendance at Motor Vehicle Crash Scenes.

The first article is by Wei Fan and it is titled "Optimizing Strategic Allocation of Vehicles for One-way Car-sharing Systems Under Demand Uncertainty." Fan's focus is on making car-sharing programs sustainable. To do so he develops a multistage stochastic optimization model to study the strategic allocation of car-sharing vehicles (OSCAV) in one-way car-sharing programs. His approach, involving a multistage linear programming model, is validated using "a seven-stage experimental network" with four car-sharing locations. According to Fan the validation provides high quality solutions suggesting that his proposed models can be used in real world applications.

In the second paper, Tony Diana studies the performance of the airports in Washington DC, and surrounding areas whose operations may result in conflicting arrival and departure paths. He defines such an area as a METROPLEX and uses it to answer several research questions. How is variation in block time affected by meteorological conditions? Are the influences of the variables affecting block times also affected by meteorological conditions? How do new air traffic control procedures and the capabilities of the next generation of air traffic control system (NEXTGEN) affect these airports? Are there differences in results when hierarchical linear models that account for fixed and random effects and regression models are used? The dependent variable in his models is block delay and the independent variables include en-route miles flown, average speed, the nation's airspace system (NAS) delays, taxi-out delays, taxi-in delays, airborne delays and percent operations in instrument meteorological conditions. He concludes from his analysis that hierarchical models provide a better picture of performance, and that instrument meteorological conditions, en-route miles flown, speed, the number of NAS delays, taxi-in and taxi-out delays have significant effects on variation in block time compared to airline flight plans.

The third paper is by Woldeamanuel and Kent and it is on the determinants of per capita vehicle miles traveled in California. Its aim is to identify policy variables which could help in reducing per capita vehicle miles traveled (VMT) and reduce greenhouse gas (GHG). Additionally, the paper aims to provide a better understanding of the factors which reduce VMT so that "state and regional organizations can develop effective strategies for near and long term per capita VMT and GHG reduction." Data for the study are from the National Household Travel Survey and include information on household demographics and travel behavior. Using multivariate regression methods the authors estimate VMT equations and employ Chow's test to reject data pooling in favor of separate models for 2001 and 2009. They find "a shift toward a more diverse group of significant

variables which explain and impact per capita VMT" (e.g., commuting by public transit, increasing public transit trips, bike trips), a group of variables with similar effects in the 2001 and 2009 models (e.g., distance to work, population density, travel day trips, and number of vehicles in a household) and concluded that their study supports compact urban development.

Park and Koo examine "the magnitudes of economic and non-economic factors in the demand for U.S. domestic air travel" in the fourth paper with the objective of analyzing carrier behavior in capturing market share. Using a utility maximization framework they derive a demand equation whose dependent variable is airline passenger miles, and its independent variables are the fares of different airlines, disposable income, seasonality, the impact of the September 11 attack and a merger variable. This demand equation is estimated with data from the first quarter of 2000 through the third quarter of 2012 drawn from sources including airlines, the Bureau of Labor Statistics and the Economic Report of the President. They find that air fare, income, seasonality and mergers are important determinants of passenger demand. More importantly, they find that U.S. airline passenger demand is unaffected by unexpected events such as the September 11 attack on airlines.

In the fifth paper Choi, Roberts and Lee write on forecasting carbon dioxide emissions in the U.S transportation sector. Their objectives are to provide forecasts of carbon dioxide at the national and state levels from 2012 to 2021 and determine if trends in carbon dioxide emissions reductions in the United States since 2000 are observable across states. Choi et al. estimate a double exponential smoothing model using data from the U.S. Environmental Protection Agency and the State Energy Data System of the U.S. Energy Information Administration to forecast carbon dioxide emissions. They find long-term trends in the reduction of carbon dioxide throughout the United States. For example, they find that carbon dioxide emissions in California are expected to decline by 25% by 2021 and emissions in Florida and Texas are also expected to decline. In 10 states, however, carbon dioxide emissions are expected to increase between 9% and 11% but these increases are not large enough to offset the general reduction in carbon dioxide emissions which this paper finds.

The sixth paper, which is on state variation in railroad wheat rates, is by Babcock, McKamey, and Gayle. Its main objective is to investigate "railroad pricing behavior for the shipment of North Dakota, Kansas and Montana wheat" and its three sub-objectives are: to develop a model to measure railroad costs and competition on rail wheat rates, measure the major determinants of rail wheat prices, and measure intermodal competition. Babcock et al. use a variant of the equilibrium model in Koo et al. (2003) in which demand is a function of railroad rates, the rates of competing modes and other demand factors, and supply of railroad service is a function of the rates of rail services and other competing modes, shipment volume, distance and other supply factors. The resulting equilibrium rate for a railroad is then a function of the rates of other competing railroads, competing modes, demand factors and supply factors. Babcock et al. estimate this rate using Kansas-Montana, Kansas-North Dakota, and Kansas-Montana and North Dakota data by ordinary least squares methods. Their results for Montana do not support the hypothesis of higher railroad wheat rates in North Dakota and Montana compared to Kansas because of lack of intramodal competition. For North Dakota they found support for the hypothesis that the railroad wheat rate is higher than the average railroad wheat rate in Kansas due to "greater intramodal competition in Kansas relative to North Dakota."

The final paper is by Tay, Kattan, and Bai and it is on the "factors contributing to police attendance at motor vehicle crash scenes." Its main hypothesis is that the "policies of the police services concerned, convenience and comfort, and expectations of injuries or driver violations will increase the likelihood of police attendance at a crash scene." They develop a logistic regression model of police attendance at crash scenes which has among its arguments, type of crash, crash severity, weather, the cost of police going to a crash scene, crash location factors, and road curvature and characteristics. The model is estimated using data for Alberta, Canada, for 2007 and the results are used to calculate the odd ratios to determine each variable's contribution to the probability of police presence at crash scenes. They find that a majority of crashes are not attended by police. For those which police attend, what makes them do so are injury severity (fatalities and injuries), if they involve hit-and-run or impaired drivers, unsafe speed, inoperable vehicles, multiple vehicles, young

male drivers, and if they occur on wet surfaces, divided roads and during afternoon peak times. Further, they found that police attendance at crash scenes is less likely if the crashes are: rear-end, angle and side-swiping, backing and passing, occur in rain and snow, during the morning peak, night-time, weekends and on roads with icy surfaces.

Michael W. Babcock
Co-General Editor

Kofi Obeng
Co-General Editor

Optimizing Strategic Allocation of Vehicles for One-Way Car-sharing Systems Under Demand Uncertainty

by Wei (David) Fan

Car-sharing offers an environmentally sustainable, socially responsible and economically feasible mobility form in which a fleet of shared-use vehicles in a number of locations can be accessed and used by many people on as-needed basis at an hourly or mileage rate. To ensure its sustainability, car-sharing operators must be able to effectively manage dynamic and uncertain demands, and make the best decisions on strategic vehicle allocation and operational vehicle reallocation both in time and space to improve their profits while keeping costs under control. This paper develops a stochastic optimization method to optimize strategic allocation of vehicles for one-way car-sharing systems under demand uncertainty. A multi-stage stochastic linear programming model is developed and solved for use in the context of car-sharing. A seven-stage experimental network study is conducted. Numerical results and computational insights are discussed.

INTRODUCTION

A successful economy relies largely upon an efficient, effective and sustainable transportation system. In many urban settings worldwide, this is increasingly highlighted, and new transportation mobility solutions are constantly being developed to accommodate increasing demands on urban infrastructure. Many Americans have realized that the price of gasoline has been increasing for years. From 2010 to 2011, this increase was 26.4% (U.S. Department of Labor 2011) and led to the largest increase of 8.0% in total transportation cost in an economy which saw a meager 1.9% growth in average annual income. In total, transportation was second only to housing and accounted for 13% of total spending (U.S. Department of Labor 2012). Though transportation's cost is increasing, many people in large urban areas do not need to fully own a vehicle because ownership invokes the expense of purchasing, licensing, insuring, and parking, which may not be justified by the little traveling they do. Some countries (e.g., Germany and Canada) have realized this and have embraced the idea of car-sharing as a short-term auto use mobility solution (Shaheen and Cohen 2007). This allows customers to use a vehicle only when they need it. Undoubtedly, this program can help alleviate urban congestion and parking issues in many cities. In particular, to create a successful car-sharing program, car-sharing operators must be able to effectively manage dynamic and uncertain demands, and make good decisions on strategic vehicle allocation and operational vehicle reallocation both in time and space to improve their profits while keeping costs under control.

The problem of optimizing strategic allocation of car-sharing vehicles (OSACV) addressed in this paper can be presented as follows. Car-sharing operators must be able to determine the most efficient means of strategically allocating vehicles at multiple car-sharing locations to accommodate future uncertain demands to maximize total expected profits. There must be a way to determine if any demand is unprofitable so as to refuse it and use resources efficiently to achieve a more favorable vehicle reallocation in the future. OSACV is a very complex stochastic optimization problem due to increasing levels of uncertainty associated with future demands. It requires car-sharing operators to not only make optimal decisions as to strategic allocation of vehicles and operational reallocation of vehicles given strategic vehicle positions, but also to anticipate the impact of such decisions in future periods.

Despite many relevant studies, no research solves the OSACV problem. Additionally, all previous studies assumed that decisions on strategic allocations of car-sharing vehicles had been made and that the vehicle supply on the first day (i.e., the initial allocation at each business location at the start of operations) was already known. In the real world, however, to maximize long-term profits, car-sharing operators must first make the best decision in terms of how to strategically allocate vehicles in space (i.e., a network of locations) to ensure they are well distributed and optimally positioned to accommodate future uncertain demands (in both time and space). After that, car-sharing operators operationally reallocate/optimize vehicles in both time (e.g., on a daily basis) and space to improve their revenues while keeping costs under control. In that regard, there is a strong need to optimize strategic allocation of car-sharing vehicles because it can have significant impacts on later car-sharing operations, which may require a large number of used vehicle movements and empty vehicle relocations to balance the fleet across locations and days based on this strategic allocation decision/input.

As such, the purpose of this paper is to develop a stochastic optimization approach to solve the OSACV problem, which is not discussed in previous studies. A multi-stage stochastic linear programming model is designed to optimize strategic allocation of car-sharing vehicles in space under demand uncertainty and is validated based on a pilot study. This validation gives results that are unique because there has never before been a study to solve the OSACV problem using stochastic programming approaches instead of simulation-based models.

The rest of this paper is organized as follows: The second section is a review of existing literature. The third presents the methodology, which includes assumptions made and stochastic linear programming model formulation for OSACV. The fourth section illustrates a scenario tree based stochastic programing solution along with the scenario tree generation, and section five describes the experimental network used in the pilot study. The sixth section discusses the computational results while the final section summarizes and discusses the results as well as provides directions for future research.

LITERATURE REVIEW

General Review of Car-sharing

Car-sharing was introduced to Switzerland in 1987, and Germany soon joined in 1988. It wasn't until 1993 that it came to North America when Quebec, Canada, created a car-sharing program. In the past 20 years, car-sharing has grown across the world (Shaheen and Cohen 2007, Shaheen et al. 2006, Carsharing 2013a, Carsharing 2013b). As of October 2012, it was present in more than 27 countries and five continents with approximately 1,788,000 individuals sharing over 43,550 vehicles (Carsharing 2013b). North America is home to 45 car-sharing programs with 26 in America and 19 in Canada. The United States has approximately 806,332 car-sharing members (Carsharing 2013b). Examples of these programs can be seen in Austin TX, Chicago IL, New York City NY, Philadelphia PA, San Francisco CA, Seattle WA, and Washington DC (Carsharing 2013a, Carsharing 2013b).

The principle of car-sharing is very simple: "Individuals gain the benefits of private vehicle use without the costs and responsibilities of ownership" (Shaheen and Cohen 2007, Shaheen et al. 2006). A car-sharing member, business owner, or household can access a a fleet of shared-use vehicles, which are located in a network of locations and are maintained by the organization that runs the car-sharing program (Shaheen and Cohen 2007, Shaheen et al. 2006). To participate, a customer purchases a membership key or card and makes an appointment by phone or Internet to use a vehicle in the fleet. Once approved, the vehicle is made available to a client who picks it up at an appointed time and leaves it at a designated car-sharing location, which may be the same as the pick-up point (one-way car-sharing systems) or anywhere in a specified zone (free-floating car-sharing systems). The customer is charged a user fee but not a maintenance fee, which is borne by the car-sharing company. In all, this program gives many people access to a fleet of shared-use vehicles without owning them.

Car-sharing has many benefits, including reduced personal transportation costs because customers only pay user fees, and it results in fewer vehicle trips, which in turn reduce traffic congestion. Other advantages are that it uses fuel efficient vehicles and in so doing, reduces fuel use and emissions, and improves roadway safety because it results in fewer vehicle miles traveled. Also, rational urban development patterns with efficient land use can be achieved because it results in fewer vehicles per capita and fewer parking locations, and it allows easy coordination of different modes of transportation, especially when their locations are near bus routes and rail stations. Finally, car-sharing provides lower income households with increased mobility by giving them the option of personal vehicle use without the expense of its ownership.

Car-sharing Fleet Management

During the past 20 years, the feasibility, operation, and safety of car-sharing have been comprehensively studied. For example, Shaheen and Cohen (2007) compared car-sharing in different countries in terms of member-vehicle ratios, market segments, parking approaches, vehicles and fuel, insurance, and technology. Their research findings are summarized below. Germany, Switzerland, and the United States distinguished themselves from their international counterparts with higher member-vehicle ratios largely due to market diversification and less active users in the United States and Germany, and inactive members in Switzerland. On-street parking in most car-sharing countries (France, and Spain) was a common form of public non-monetary operator support. And, although there were distinct regional differences in alternative fuel vehicle use, conventional gasoline automobiles accounted for most of the fleets (except in Japan and Spain).

Barth and Todd (1999) simulated car-sharing programs that included the ability to calculate vehicle availability, vehicle distribution, and energy management. They applied this to a resort community in Southern California and found that the shared vehicle system was most sensitive to the vehicle-to-trip ratio, the relocation algorithm used, and the charging scheme employed. Their preliminary cost analysis indicated that such a system could be very competitive with present transportation systems (e.g., rental cars, taxis, etc.). Kek et al. (2006) also used simulation to investigate car-sharing by emphasizing operator-based relocation techniques. They were able to help operators maximize efficiency and increase service levels and validated their model using data collected by an operational car-sharing company in Singapore.

In later work, Kek et al. (2009) presented a simulation-based decision support system to determine a set of near-optimal manpower and operating parameters for vehicle relocation operations in car-sharing systems. They tested their approach in Singapore and reported that it resulted in a 50% reduction in staff cost, a reduction in zero-vehicle-time (i.e., time when stations have no vehicles available) ranging between 4.6% and 13.0%, a maintenance of the already low full-port-time, and a 37.1%-41.1% reduction in number of relocations. Nair and Miller-Hooks (2011) and Nair et al. (2013) presented some interesting optimization work for vehicle and bike sharing, respectively. In a real-world application of their work to a system in Singapore, they found that fleet management strategies which explicitly accounted for the stochastic nature of demand offered greater reliability than strategies based on static methods. Also, fleet redistribution strategies based on their approach were better than those from scenarios in which demand outstripped supply. Despite these studies, few have applied stochastic programming models for car-sharing fleet management (by optimizing strategic vehicle allocation), though such an approach has been widely used in general fleet management research.

Review of Stochastic Programming and its Applications in Fleet Management

The stochastic dynamic vehicle allocation problem (SDVAP) for car-sharing has been studied in the past because it is common in freight and other transportation industries. Some of these studies involve static deterministic, static stochastic, and dynamic deterministic formulations as well as

dynamic vehicle allocations under uncertainty and potentially infinite time horizons. However, very few studies have been done on dynamic stochastic formulations of the car-sharing problem. Among them, Dejax and Crainic (1987) presented a taxonomy of empty vehicle flow problems and models and conducted a comprehensive review of the existing literature on the subject. Major research trends and perspectives were identified, and the advantages of a hierarchically integrated approach for simultaneous management of empty and loaded freight vehicle movements were also discussed. Jordan and Turnquist (1983) discussed uncertainties in vehicle supply and demand and proposed a system for railroad freight cars to optimize their allocations, which was solved with the Frank-Wolfe algorithm. This iterative algorithm uses linear approximations to a nonlinear objective function and solves it as linear programming sub-problems until it converges to an optimal solution for a nonlinear (possibly concave) objective function.

Powell (1986) and Fantzeskakis and Powell (1990) used stochastic formulation of SDVAP and proposed a heuristic algorithm which contrasted various deterministic approximations. This algorithm used a rolling horizon procedure to simulate the operations of railroads and truck carriers. They conducted experiments for a 12-day period for different fleet sizes, and their numerical results indicated the superiority of their algorithm to other approaches they tested in terms of total profit. Bookbinder and Sethi (1980), Cheung and Chen (1998), Cheung and Powell (2000), and Fan and Machemehl (2007) studied SDVAP using dynamic stochastic formulations and suggested that they had advantages over their counterparts and should be studied further.

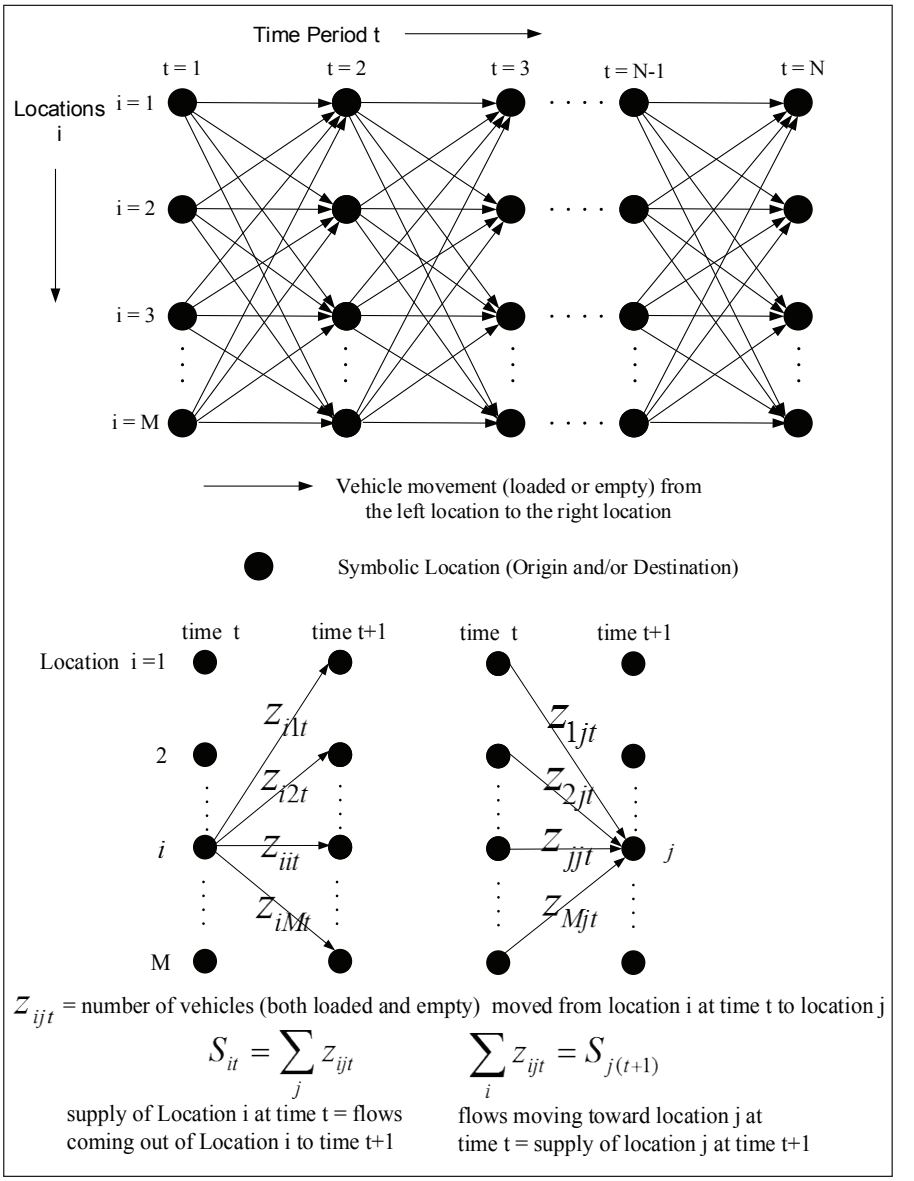
Although these previous studies are very helpful, little has been done on using stochastic optimization techniques managing and operating car-sharing programs. An exception is Fan et al. (2008), who studied SDVAP to maximize profits for a car-sharing service operator. To do this, developed a multi-stage stochastic linear integer model and solved it with a Monte Carlo sampling-based stochastic optimization method in which Monte Carlo simulation was used to realize uncertain demands that were assumed to be Poisson distributed. The car-sharing dynamic vehicle allocation problem was solved and fleet management was optimized in both time and space. As a pilot study, a five-stage example network with four car-sharing locations was designed to test the developed method. The computational results indicated a high-quality SDVAP solution, suggesting that the algorithm could be used for real-world applications. Fan (2013) later developed a stochastic optimization framework to address SDVAP for car-sharing systems. Rather than using Monte Carlo sampling methods, he assumed uncertain demands to be discretely distributed, generated a complete scenario-tree, and solved it using stochastic optimization techniques. The computational results indicated a high-quality solution, suggesting that stochastic optimization can be used in real-world applications. Of note is that both studies dealt with the dynamic vehicle allocation on a day-to-day operational level, and assumed that strategic vehicle allocation (i.e., the vehicle supply) across a car-sharing network was given. Also, both studies were based on large-scale linear and multi-stage stochastic programming theory found in Dantzig (1955), Dantzig and Wolfe (1960), Ziemba (1970), Wollmer (1980), Wets (1983), Birge (1985), Birge and Louveaux (1997), Wallace (1986), and Beale et al. (1986). Scenario trees are important parts of this technique, and Zenios (1998), Kouwenberg (2001), Hoyland and Wallace (2001), and Fleten et al. (2002) developed such trees for multi-stage stochastic programming decision problem scenarios.

METHODOLOGY

To study the OSACV problem, several assumptions are made in this paper. Some are that customers reserve vehicles at the end of each day, specific pickup locations are used by customers who can drop off cars at any specified (it can be the same or different) location at a specific time (one day after pick up), and one vehicle is allocated per demand per customer. The vehicles are in use, in transit empty or stationary empty, and the travel time between all car-sharing locations is one day, whether a vehicle is in use or empty. Though no future information is available to car-sharing managers, the expected (i.e., mean) demand at the beginning of each day throughout the decision horizon (when the strategic allocation of vehicles decision is to be made) is always known. Furthermore, it

is assumed that though the mean values and probability distribution of uncertain demands between all pairs of car-sharing locations are not necessarily equal, they are known and discretely distributed (e.g., can be classified into and labeled as HIGH, MEDIUM, and LOW demand scenarios). And, it is assumed that on all days of operation, every vehicle is available for use, that the expected (i.e., mean) demands between all pairs of car-sharing locations at all times can be forecasted and determined based on relevant market surveys, and the demands on different days may be independent of each other, or can be correlated. Nonetheless, all daily car-sharing demand forecasts are assumed to be known and used as inputs to the OSACV model, and future vehicle availability is directly affected by current strategic allocation decisions on vehicle use. From these assumptions, the formulation of OSACV and the graphs of the network studied are in Figure 1. The profit from servicing demand is the difference between the revenue collected and the cost incurred. Also, "flow of vehicles" and the "number of vehicles" are equivalent as each vehicle only carries one passenger.

Figure 1: Network Flow Representation of the OSACV



Model Formulation

Based on the assumptions, a stochastic programming formulation of the OSACV problem is in Table 1 for a planning horizon of N days.

Table 1: Definition of Terms

Indices/Sets	
$i, j \in$ R	Regional carsharing pick-up origins and/or drop-off destinations
$t \in$ T	Time periods
$w \in$ W	Demand scenarios, in which each demand scenario consists of a complete realization set of specific demands at each stage
Random Variables	
$\tilde{d}_{ijt}$	Random demand denoting the number of customers needing transportation from location i to location j during period t, $t = 2,\ldots,N$
Parameters/Data	
r_{ij}	Net revenue for satisfying a carsharing demand from pickup location i to dropoff location j
c_{ij}	transfer cost of moving empty from location i to location j
L_{ij1}	Number of carsharing requests known at time $t = 1$ to be available moving from location i to location j at the first time period during the current planning horizon
d^w_{ijt}	Demand denoting the number of customers needing transportation from location i to location j during period t under demand scenario w, $t = 2,\ldots,N$
p^w	Probability of demand scenario $w \in$ W
Decision Variables	
x^w_{ijt}	Number of carsharing vehicles that are used by customers from location i to location j, during period t under demand scenario w, $t = 1,2,\ldots, N$
y^w_{ijt}	Number of carsharing vehicles moving empty from location i to j, during period t under demand scenario w, $t = 1,2,\ldots, N$
$Z^w_{ijt} = x^w_{ijt} + y^w_{ijt}$	Number of carsharing vehicles moving loaded or empty from location i to location j, during period t under demand scenario w, $t = 1,2,\ldots, N$
S_{i1}	Strategic allocation/supply of carsharing vehicles at location i at the beginning of period 1
S^w_{it}	Supply of carsharing vehicles at location i at the beginning of period t under demand scenario w, $t = 2,\ldots, N$

Objective function: The optimization model for the strategic allocation of car-sharing decision-making problem for each period t = 1, 2, …, N can be presented as follows:

(1) $$h(S_{i1}, x_{ijt}^{w}, y_{ijt}^{w}, d_{ijt}^{w}) = \max_{S_{i1}, x_{ijt}^{w}, y_{ijt}^{w}} \sum_{i}\sum_{j}\sum_{t}\sum_{w} (r_{ij} x_{ijt}^{w} - c_{ij} y_{ijt}^{w}) * p^{w}$$

(1a) subject to: $x_{ij1}^{w} \le L_{ij1}$ $\quad i \in R, j \in R, w \in \mathrm{W}$

(1b) $x_{ijt}^{w} \le d_{ijt}^{w}$ $\quad i \in R, j \in R, t = 2, 3, \ldots, \mathrm{N}, w \in \mathrm{W}$

(1c) $\sum_{j} (x_{ijt}^{w} + y_{ijt}^{w}) = S_{it}^{w}$ $\quad i \in R, t = 2, 3, \ldots, \mathrm{N}, w \in \mathrm{W}$

(1d) $\sum_{j} (x_{ij1}^{w} + y_{ij1}^{w}) = S_{i1}$ $\quad i \in R, w \in \mathrm{W}$

(1e) $\sum_{i} (x_{ijt}^{w} + y_{ijt}^{w}) = S_{j(t+1)}^{w}$ $\quad j \in R, t = 1, 2, \ldots, \mathrm{N}\text{-}1$

(1f) $x_{ijt}^{w}, y_{ijt}^{w}, S_{it}^{w} \ge 0$ $\quad i \in R, j \in R, t = 1, 2, \ldots, \mathrm{N}, w \in \mathrm{W}$

(1g) $x_{ijt}^{w}, y_{ijt}^{w}, S_{it}^{w}$ must be integers $\quad i \in R, j \in R, t = 1, 2, \ldots, \mathrm{N}, w \in \mathrm{W}$

As can be seen, the objective function is to maximize total expected profits. The cost of unmet demand is not considered but can be easily incorporated if desired by including a penalty in the objective function. Constraints (1a) and (1b) state that all loaded movements serving the transportation needs of car-sharing customers must be less than or equal to the requested demand for those movements under each scenario for all periods. Constraints (1c) and (1d) indicate that the total number of loaded and empty vehicles that move out of a location i at any period t must be equal to the total vehicles available at location i during all future periods under each scenario, or the number of strategically allocated vehicles during the first period. Constraints (1e) represent flow conservation properties, which guarantee that the number of vehicles available at location j at period t + 1 must be equal to the number of loaded or empty movements to location j during period t under each scenario. Constraints (1f) and (1g) represent non-negativity and integer properties, respectively. In particular, for OSACV, the strategic allocation/supply of car-sharing vehicles at location i at the beginning of period one is a decision variable which can be optimally solved and determined by the model as presented above. Once such a strategic vehicle allocation decision has been made, the number of vehicles allocated across all locations in the car-sharing network is used as an input to determine the optimal car-sharing vehicle reallocation pattern at the operational (e.g., day-to-day) level for all future periods.

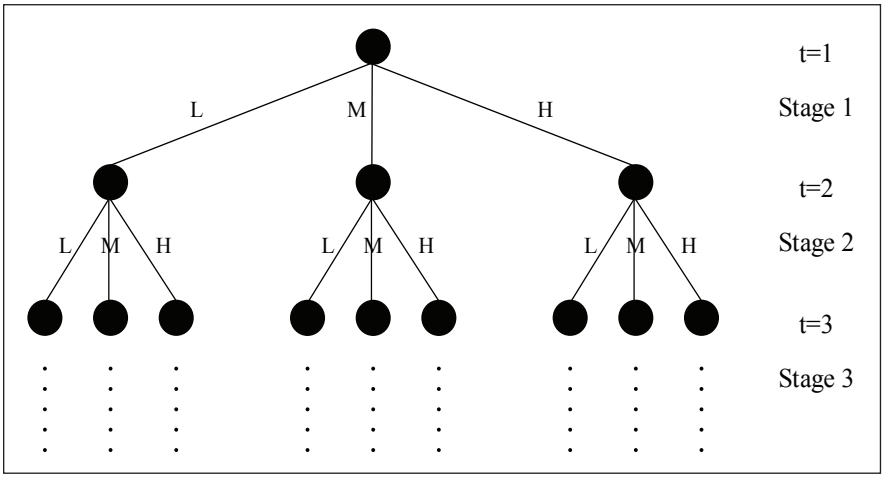
Problems involving uncertainty in the objective function and/or constraints fall in the domain of stochastic programming. Furthermore, it can be seen that OSACV is a linear programming problem with uncertain constraint coefficients on the right-hand side. The major difficulty arising from this problem is the required truncation of their infinite planning horizon to a finite number of periods (N), which might cause deviations from the infinite planning horizon's optimal solution. Because of this, OSACV can be treated as a multiple-stage (here N-stage) Stochastic Linear Programming (SLP) problem in which a decision made in the following stage can compensate for any bad effects that might have been experienced as a result of the previous-stage decision. Several approaches have been proposed to solve multiple-stage SLP. When the problem size is manageable, the simplex, interior point and decomposition methods are generally very efficient in solving it (Birge and Louveaux 1997).

SOLUTION APPROACH

Figure 2 illustrates a complete scenario-tree-based approach for solving the multi-stage stochastic programming models. The nodes in the tree represent states at a particular period, t. Decisions are made at the nodes, and the arcs represent realizations of uncertain variables. Decisions to be made further down the scenario tree depend on those already made through parent nodes and the uncertain properties of descendant nodes, such as the three L(ow), M(edium), and H(igh) car-sharing demand scenarios shown. The generation of the scenarios is based on the assumed discrete distribution, and decision makers can specify the probability distribution function so that the statistical properties of the problem are preserved. A complete scenario tree consists of realizations of the uncertain variables of each period (or stage). In practice, only the first-stage solution at the top node is used for decision making. Decisions at stage two or after are only done to find the right incentives for the first-stage decisions (Fleten et al. 2002).

At the beginning of the first period, decisions are made based on current information (and realizations of the stochastic future) and at the end, the effects of these decisions are seen. Given these effects and new information for the next period, a new decision is made. Based on the consequences from the second period decisions and given new information for the third, a decision is made again. The whole process continues indefinitely in principle. For each scenario tree with generated random variates, one can use exact optimization methods (e.g., L-shaped Method – see Birge and Louveaux 1997) to solve it. In fact, the first-stage decision is obtained by developing and running an SAS macro-based SAS/OR PROC OPTMODEL code (SAS 2011).

Figure 2: Scenario Tree Approach for Solving the Multi-stage Stochastic Programming Models



EXPERIMENTAL DESIGN

A car-sharing dynamic vehicle allocation problem represented by a seven-stage experimental network (specifically, a planning horizon of seven days and four car-sharing locations) was designed as a pilot study to test the quality and efficiency of the solution using the developed stochastic programming method to solve OSACV. As presented in the model formulation section, the demands at each car-sharing location on the first day are assumed to be known with certainty, and the expected (i.e., mean) values of the uncertain car-sharing demands on days two to seven are assumed to be known and used as input to OSACV. As mentioned, all stochastic demands on days two to seven are assumed to follow a discrete distribution, which constitutes three-level (HIGH, MEDIUM, and LOW) demand scenarios. All the supply and demands are expressed as units of "vehicles." The net

revenue per loaded vehicle and the cost per empty vehicle are expressed as matrices in dollars. The input required for the OSACV example is summarized in Table 2.

To solve OSACV, the expected value of the uncertain demand (i.e., the mean demand as shown in Table 2) is used as the known initial demand on the first day. This is deemed reasonable because car-sharing operators only need the mean demand to make strategic vehicle allocation decisions. However, once such a strategic vehicle allocation decision has been made, the number of vehicles allocated across locations in the car-sharing network is used as an input to determine the optimal car-sharing vehicle reallocation pattern at the operational (e.g., day-to-day) level for all future periods.

Table 2: Input to the OSACV Example

Mean Demand for All Following Days (Unit: Vehicles)		Drop-off Destination			
		1	2	3	4
Pick-up origin	1	11	8	7	15
	2	5	9	12	8
	3	10	12	11	7
	4	10	17	10	16

Stochastic High Demand (Prob=0.4) (Unit: Vehicles)		Drop-off Destination			
		1	2	3	4
Pick-up origin	1	16	14	10	22
	2	8	14	18	12
	3	16	18	15	11
	4	15	24	15	25

Stochastic Medium Demand (Prob=0.2) (Unit: Vehicles)		Drop-off Destination			
		1	2	3	4
Pick-up origin	1	13	6	7	15
	2	5	9	12	10
	3	10	12	11	9
	4	10	15	10	14

Stochastic Low Demand (Prob=0.4) (Unit: Vehicles)		Drop-off Destination			
		1	2	3	**4**
Pick-up origin	1	5	3	4	8
	2	2	4	6	3
	3	4	6	7	2
	4	5	11	5	8

Net Revenue (Unit: $)		Drop-off Destination			
		1	2	3	4
Pick-up Origin	1	8	12	19	15
	2	10	11	18	17
	3	14	16	9	19
	4	15	17	19	12

Transfer Cost (Unit: $)		Drop-off Destination			
		1	2	3	4
Pick-up Origin	1	0	3	4	4
	2	3	0	4	5
	3	4	4	0	4
	4	4	5	4	0

Initial Total Supply (Unit: Vehicles)	171

The strategic car-sharing vehicle allocation decision-making problem in this example is a typical multi-stage stochastic programming problem. Although it involves dynamic vehicle allocations in only seven periods and at only four car-sharing locations, it is not a minor problem. For example, assume a three-level case in which the demand at each stage has three associated situations, namely HIGH, MEDIUM, and LOW. Then, the total number of decision variables involved in all scenarios of this problem is the sum of $(3^0 + 3^1 + 3^2 + 3^3 + 3^4 + 3^5 + 3^6) * 4^2$ loaded vehicle movement decisions, $(3^0 + 3^1 + 3^2 + 3^3 + 3^4 + 3^5 + 3^6) * 4^2$ empty vehicle movement decisions, four strategic vehicle allocation decisions and $(3^1 + 3^2 + 3^3 + 3^4 + 3^5 + 3^6) * 4^1$ operational vehicle reallocation decisions, which are 39,348 decisions altogether.

RESULTS AND DISCUSSION

Strategic Allocation of Car-sharing Vehicles

Stochastic Programing Approach. The stochastic programing (SP) solution has been developed and had its quality tested. As mentioned, SP is a modeling framework for handling uncertainty in some of the problem data (e.g., the stochastic demand in this paper). Once a scenario tree has been set up with car-sharing demands between origin-destination pairs with three levels (i.e., low, medium, and high) during all periods, an exact stochastic optimization method (e.g., L-shaped method) is used to solve the OSACV problem and obtain the first-stage decision. Since future car-sharing demands are stochastic (although with some known discrete probabilities) and a decision must be made at the current period (i.e., Stage 1), the values of all first-period decision variables must be the same for all scenarios. Using the developed SAS macro code, the solution obtained for the three-level case shown in Table 3 is SP of $14,664 for all possible scenarios. This value means that one can earn $14,664 on average if such SP strategic vehicle allocation decision is used.

Table 3: Numerical Results

	Solution Approaches	Solution Descriptions	Objective Function Values
Developing Solutions	Deterministic Optimization	Expected Demand (ED) (i.e., Optimize the average scenario)	$16,460
		Wait-and-See (WS)	$14,718
	Stochastic Programming	Stochastic Programming (SP) under Three Scenarios: HIGH, MEDIUM and LOW	$14,664
Processing Solutions	Evaluating Solutions under Stochastic Environment	Evaluating ED (EED)	$14,641
Comparing Solutions	Value of Perfect Information (VPI)	VPI = WS - SP	$54
	Value of Stochastic Solution (VSS)	VSS = SP - EED	$23

Deterministic Optimization Approach

Deterministic optimization (DO) solutions, including the expected demand (ED) solution and wait-and-see (WS) solution, were also developed.

Expected Demand Solution. It is common to ignore the uncertainties associated with system parameters because of computational inconveniences they cause and instead develop heuristic decisions using the expected value of the random variables. In other words, car-sharing operators may make the decision to calculate the weighted average demand of the three scenarios as shown in the above example and then execute the optimal solution by optimizing the "average" scenario. By doing so, the OSACV problem is solved by replacing random demands with their expected values and the solution in Table 3 shows a profit of $16,460. This is expected because the problem has changed from stochastic programming to deterministic optimization. When demand is deterministic instead of random, one has certain demand information and, as a result, one can get a better solution compared with the stochastic programming approach with an objective function value of SP equal to $14,664. Also, the value of the objective function for the expected value problem is greater than that of the stochastic problem (for this profit maximization OSACV problem), which accords with Jensen's inequality principle (Birge and Louveaux 1997) commonly used in the trucking industry, where first-stage decisions are usually made based only on expected demand.

Wait-and-See Solution. Assuming that perfect information can be obtained, that is, stochastic demands are now deterministically known for all origin and destination pairs throughout the entire optimization period for all scenarios, then OSACV changes to a deterministic model (sometimes called the wait-and-see strategy) whose solution provides an upper bound for the optimal SP for maximization problem (Birge and Louveaux 1997). By solving several separate stochastic linear programming models, each consisting of a separate (unrelated) scenario tree with realized demand information, the wait-and-see (WS) solution results as shown in Table 3 is a profit of $14,718, which is greater than that of the stochastic problem. This is expected because one can always earn more if perfect information about demand at each stage is known. Furthermore, the WS provides a tighter upper bound than the expected demand problem, which is predicted by the theorem that WS $\leq$ ED (again for the maximization problem) if only right-hand-side variables are random (Birge and Louveaux 1997).

Comparing SP and DO Solutions

Comparing Decision Results. The optimal solution developed using the SP approach is as follows: 41 vehicles should be allocated to location 1, 34 to 2, 40 to 3, and 56 to 4. On the other hand, the DO-ED approach gives a different solution: 41 and 40 vehicles are still allocated to locations 1 and 3, respectively. However, 30 vehicles are allocated to location 2 and 60 vehicles to 4. These

clearly show that different solutions would be obtained if different approaches are used to solve the OSACV problem.

In addition, the recommended vehicle allocation with the first day's demands by both solution approaches show that some demands are refused and some vehicles are assigned to move empty. This is expected because the goal to maximize profits results in unprofitable demands (with lower profit) not being satisfied and spare empty vehicles allocated to a more favorable future location. While this may not be exactly parallel to current car-sharing management practices (in which all car-sharing demands are typically served even when some are not profitable), the results certainly can be extended to a real-world car-sharing management system.

Value of Perfect Information. Executing the SP solution puts the car-sharing company in the best position to handle any demand scenario that might occur in the future. However, if the future can be forecasted, then the car-sharing company could optimize its solution separately for any of the scenarios in the wait-and-see solution. The difference between the deterministic "wait-and-see" and the SP solutions is commonly known as the Value of Perfect Information (VPI) (Birge and Louveaux 1997). In this regard, VPI can be calculated as VPI = WS – SP = $54, which is the total amount a car-sharing fleet manager is willing to pay to obtain perfect information on system demands for all periods.

Value of Stochastic Solution. The difference between the SP solution's cost and the total cost of using the "expected demand" solution (where the solution for the expected demand case is used as the "average" scenario solution and evaluated under stochastic environment) corresponds to the Value of Stochastic Solution (VSS). In other words, if the solution of the expected demand problem is evaluated in the random demand environment, the objective function of the stochastic problem becomes EED of $14,641, which is actually worse than the SP solution (SP = $14,664). That is, VSS can be calculated as VSS = SP – EED = $23, which can be explained as the cost of ignoring system demand uncertainty and always using their expected values instead. Although this amount might not seem large, the aggregate value for a large network under a long time horizon can be significant. Therefore, stochastic solutions are always preferable to expected demand solutions.

Computation Efficiency. As described above, the SP approach has been used to solve the OSACV problem in this paper. One of its promising properties is that execution time is very short. It takes only about 10 seconds for the SAS code execution of the example network. Furthermore, as previously shown, the computational quality of the solution is very good. These two characteristics strongly suggest that this stochastic programming approach could be applied to solve the OSACV problem efficiently and effectively.

CONCLUSIONS AND FUTURE RESEARCH

Car-sharing offers an environmentally sustainable, socially responsible, and economically feasible mobility form in which a fleet of shared-use vehicles in a number of locations can be accessed and used by many people rather than a single owner on an as-needed basis at an hourly or mileage rate. It allows users to enjoy the benefits of having personal vehicles but without the responsibilities and costs of ownership. This paper develops a stochastic optimization approach to solve the optimal strategic allocation of vehicles for one-way car-sharing systems, in which operators must be able to effectively manage dynamic and uncertain demands, strategically make the best decision in allocating vehicles, and operationally optimize vehicle reallocation both in time and space to improve their revenues while keeping costs under control. A multi-stage stochastic linear programming model with recourse is created and solved for use in car-sharing under demand uncertainty. A seven-stage example network with four car-sharing locations is designed to test the SP approach. The computational results indicate high quality OSACV solutions, suggesting that the SP algorithm can be used for real-world applications. Further research validating the SP formulation for the OSACV

problem using real-world large networks will be useful. In addition, archived historical data can be used to validate it and additional constraints may be incorporated in the optimization model.

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Measuring Performance at a Large Metropolitan Area: The Case of the DC (District of Columbia) Metroplex

by Tony Diana

Hierarchical linear models improve the measurement of performance when applied to a construct such as a metroplex. It compares the outcomes of a hierarchical linear model with those of a multiple regression model to evaluate whether meteorological conditions at individual airports and overall would explain variations in block delays. The study used the cases of the three largest airports in the DC Metroplex and concluded airborne delays had a significant random effect on block delays in spite of meteorological conditions at each airport. It pointed out that surface operations efficiency played a significant role in explaining variations in block delays.

INTRODUCTION

The National Airspace System (NAS) consists of a network of airports that serve the needs of a variety of users (i.e. air carrier, air taxi, general aviation, military, and freight operators). These airports are sometimes clustered within large metropolitan areas, also called "metroplexes," where a mix of users and aircraft sizes raises some challenges for air traffic control (ATC) as they share the same airspace.

A metroplex can be defined as a metropolitan area where access among larger hub and smaller general aviation airports in close proximity may be affected by interdependent and sometimes conflicting arrival and departure routes. The appendix provides an illustration of the arrival and departure streams at the DC Metroplex. The metroplex concept holds a central place in the Next Generation Air Transportation System, or "NextGen," that aims to transform the legacy radar-based air traffic control into the future satellite-based air-traffic-managed system. In 2009, the RTCA (Radio Technical Commission for Aeronautics)[1] Task Force 5 identified 21 areas "to optimize area navigation (RNAV) and required navigation procedures (RNP) operations, and institute tiger teams that focus on quality at each location as well as integrate procedure design to de-conflict airports and expand use of terminal separation rules."[2] Such is the case in this study of the District of Columbia Metroplex, or DC Metroplex, that includes (1) large hub airports such as Baltimore/Washington International Thurgood Marshall (BWI), Washington Reagan National (DCA), and Washington Dulles International (IAD) airports; (2) secondary airports such as Richmond International (RIC); and (3) general aviation airports such as Frederick Municipal (FDK), Martin State (MTN), and Manassas Regional (HEF) airports, among others.

The Federal Aviation Administration (FAA) initiated the airspace redesign project of the DC Metroplex in September 2010. After proceeding through the phases of study, design, environment, and safety management system, the implementation of airspace redesign started in July 2013. In the meantime, new arrival and departure procedures were implemented to support area navigation (RNAV) and optimized profile descent (OPD), as well as to minimize conflicting flight paths. Optimized profile descents allow aircraft to stay longer in level flight and to descend progressively from the top of descent to the runway threshold. OPDs serve two major purposes: (1) Reduce stepwise descent that increases fuel consumption and (2) minimize the need for frequent read-back communication between pilots and air traffic controllers.

The present analysis focuses on the cases of the three largest airports in the DC Metroplex (BWI, DCA, and IAD) at three different time periods: before the implementation of NextGen capabilities and new flight procedures (summer 2007) and afterward (summer 2012 and 2013). The summer months of June to August were selected because they are characterized by peak traffic and extreme weather such as thunderstorms. This study assumes that variations in block delays are likely to be impacted by en-route miles flown, aircraft speed, the counts of NAS-related delays, taxi-in and -out delays, as well as the percentage of operations in instrument meteorological conditions. The study also hypothesize that meteorological conditions at each airport and overall for the metroplex are likely to affect block delays when considering the random effects of airborne delays. This study attempts to answer the following research questions:

- How much of the variation in block delays (the difference between actual and filed block times) can be attributed to meteorological conditions during the hours of 07:00 to 21:59 for each sampled time period?
- Is the influence of any independent variables on block delays more likely to vary under specific meteorological conditions (instrument vs. visual) overall and at each individual airport for each sampled summer?
- Is there any significant change in block delays at the Metroplex and individual airport levels as new procedures and NextGen capabilities have been implemented?
- Is there any difference between the outcomes of a hierarchical linear model based on a mixed model and those of a multiple regression model?

To answer these questions, a two-level hierarchical linear model utilizing fixed and random effects was selected. A hierarchical linear model implies that meteorological conditions are nested within each sampled airport. Hierarchical linear or multilevel analysis[3] models have been widely used in spatial analysis, sociology, and psychology, but not extensively in aviation. This study serves several purposes: (1) it illustrates how hierarchical analysis provides some better insight into the factors that explain block delays; (2) it takes into account multiple levels of measurement that would otherwise be "hidden" in an ordinary least-squares model; and (3) it includes fixed-effects and random-effects variables.

Beaubien et al. (2001) provided a review of hierarchical linear modeling techniques applied to commercial aviation research with pilot, crew, and airlines as the three levels of analysis. Haines et al. (2002) determined that chronic exposure to aircraft noise was likely to be associated with poor school performance in reading and mathematics performance. Castelli et al. (2003) resorted to multilevel analysis to evaluate the patterns of variation of price elasticity of demand among the various routes of an airline and concluded that the airfare elasticity of passenger demand significantly varied among the different routes of the airline. Gudmunsson (2004) evaluated the factors associated with airline performance using a two-level bottom–up hierarchical approach. Miranda et al. (2011) used multilevel analysis to investigate the blood lead levels among children living in six North Carolina counties resulting from the exposure to aviation gasoline exhaust. Chung and Wong (2011) investigated the impact of China-Taiwan non-stop routes on cross-strait air travel city pairs. Fidell et al. (2011) utilized multilevel models to assess the impact of annoyance with aircraft noise exposure across communities. Rozenblat et al. (2013) made use of multilevel clustering methods to delineate the effects of geographical distance, hubs, network densities, and bridges on worldwide air passenger traffic.

The next section will deal with the methodology and assumptions underlying the analytical models before discussing the model outcomes and providing some final remarks and implications for future research.

METHODOLOGY

The Models' Variables and Data Processing

The sample includes 828 observations equally divided into three summers (92 days each) and three airports. All variables originate from the Aviation System Performance Metrics (ASPM) data warehouse. ASPM reports operational and delay metrics from a variety of sources: OPSNET (Operational Network), Traffic Flow Management System (TFMS), and the Bureau of Transportation Statistics (BTS). Within each day, the selected variables were measured from the hours of 07:00 to 21:59 when traffic is most active. Each hour was flagged for instrument versus visual meteorological conditions. Since weather is the major driver of delays, this study assumed that it was not possible to measure variations in block delays as explained by the model without isolating the impact of meteorological conditions as a whole and for each selected airport in the metroplex.

The number of variables was determined by comparing Akaike's Information Criterion (AIC), Akaike's Information Criterion corrected for finite sample sizes (AICC) and Schwartz's Bayesian Information Criterion (BIC) of the various models. The lower the number of estimated parameters, the lower the value of the AIC and BIC and, as a result, the better the fit of the model. Other considered variables were the number of operations, gate arrival and departure delays, and excess miles flown. The final models included the following variables:

- *Block delays* represent the dependent variable. They are computed as the difference between actual and block times filed in the flight plan, in minutes. The flight plan used to compute block delays is the last one before takeoff. Block time measures the duration from gate-out (origin) and gate-in (destination) times. Block delays include all the flights that arrive at BWI, DCA, and IAD during the hours of 07:00 to 21:59 (local time). The comparison of actual with flight-planned times removes from the analysis any biases due to airlines' schedule padding if actual block times had been compared with scheduled block times. However, it is important to point out that the number of scheduled operations for the combined airports declined from 214,306 in summer 2007 to 207,127 in summer 2012 and 204,894 in summer 2013 (sources: Innovata flight schedules).
- *En-route miles flown* represent the distance about 100 nautical miles from the origin airport to 100 nautical miles from the destination airport.
- *Speed* is the average number of nautical miles flown per hour for aircraft flying into BWI, DCA, and IAD.
- *The counts of National Airspace System or NAS-related delays* account for "the delays and cancellations attributable to the national aviation system that refer to a broad set of conditions, such as non-extreme weather conditions, airport operations, heavy traffic volume, and air traffic control."[4] These delays often impact changes in the flight plan.
- *Taxi-out delays* are the differences between actual and unimpeded gate-out to wheels-off times, in minutes. Unimpeded taxi-out times are based on taxi-out times reported by the major carriers to BTS, and they estimate the time it takes for an aircraft to move from the gate departure to takeoff when there is only one aircraft ahead in the takeoff queue. The gate-out, wheels-off, wheels-in, and gate-in messages used to compute the actual times of the flight phases are compiled by ARINC (Aeronautical Radio, Incorporated), a division of Rockwell Collins (http://www.airinc.com) and recorded in the ASPM data warehouse.
- *Taxi-in delays* are the differences between actual and unimpeded wheels-on to gate-in times, in minutes. The computation of taxi-in delays are based on the same principles as taxi-out delays.
- *Airborne delays* measure the difference between actual airborne times and the flight plan's estimated time en route, in minutes. Airborne delays are sometimes used by ATC to provide safe separation, regulate speed, merge traffic, and avoid potential conflicts among flight paths.

Airborne delays characterize the random effect variable in the model, which implies setting up a common correlation among all observations having the same level of airborne delays.

- *The percentage of operations in instrument meteorological conditions* is derived from the minimum ceiling and visibility in effect at each facility summarized in Table 1. If the percentage of operations in instrument meteorological conditions during a specific hour is greater than 10%, then the dummy variable "IMC" for that flight record is coded as "1" and "0" otherwise.

Table 1: Selected Airports' Minimum Ceiling and Visibility

Airpot	Ceiling (ft)	Visibility (nm)
BWI	2,500	5
DCA	3,000	4
IAD	3,000	7

Source: FAA, ASPM

The hierarchical linear model estimates were derived with the MIXED procedure, while the multiple regression models used the REG procedure, both programmed in SAS®. Meteorological condition and airport are the classification variables that represent the two levels in this analysis. The hierarchical linear model estimates were generated with maximum likelihood. Fifteen iterations were required for convergence.

This study utilizes a mixed model that includes fixed-effects parameters (known explanatory variables) and covariance parameters that are useful when data are grouped into clusters (i.e., individual airport and meteorological conditions at selected airports) in which data are likely to be correlated. The clustering (nesting) of meteorological conditions into the airport variable creates additional potential variability and correlation. Although data are assumed to have a normal distribution, the mixed model allows correlation and heterogeneous variances.

The Hierarchical Model Assumptions and Specifications

An ordinary least-squares (OLS) regression model does not provide any indication of how the selected factors account for variations in block delays when data are sliced at different levels (i.e. by meteorological condition and by meteorological condition at each sampled airport). A hierarchical linear model enables analysts to account for the variations of block delays and to understand the contribution of meteorological conditions at each sampled airport to explain the variation in block delays. Readers interested in hierarchical linear or multilevel analytical models are referred to Bryk and Raudenbush (2001) and Hox (2010) for a clear exposition.

Hox (2010: 4) summarized the purpose of multilevel analysis in these terms: "The goal of the analysis is to determine the direct effect of individual- and group-level explanatory variables, and to determine if the explanatory variables at the group level serve as moderators of individual-level relationships." Hierarchical linear models provide the following benefits:

- They improve the estimation of effects within individual airports.
- They allow analysts to test the hypotheses of cross-level effects and the partitioning of variance and variance components among the two levels.
- One of the key assumptions of OLS is independence of observations. However, nesting meteorological conditions into airports creates dependencies in the data and may generate inaccurate estimates in non-hierarchical linear models. The dependence of observations may entail biased parameter estimates and standard errors in OLS models.
- It is important for analysts to understand variations at different hierarchical levels. Hierarchical linear analysis takes into account the correlated nesting of data, whether block delays vary based on meteorological conditions at a specific airport during a specific time period.

The hierarchical linear model that features a random intercept and slopes for each time period features two levels:

Level 1 for Each Selected Time Period:

(1) $Y_{ij} = \beta_{0j} + \beta_{1j} X_{1j} + \ldots + \beta_{ij} X_{ij} + \varepsilon_{ij}$

Where $\varepsilon_{ij} \sim N(0, \sigma^2)$, Y_{ij} represents block delays and X_{ij}, the factors in specific meteorological conditions nested at j airport that explain variations in block delays.

Level 2 for Each Selected Time Period:

(2) $\beta_{0j} = \Upsilon_{00} + U_{0j}$

(3) $\beta_{1j} = \Upsilon_{10} + U_{1j}$

Where $\begin{bmatrix} U_{0j} \\ U_{1J} \end{bmatrix} = U_j \sim N\left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_0^2 & \tau_{10} \\ \tau_{10} & \tau_1^2 \end{bmatrix}\right]$ independent over j and with ε_{ij}

τ_0^2 represents the variance of the level two residuals U_{0j} from predicting the level 1 intercept (β_{0j}). τ_1^2 is the variance of the level 2 residuals U_{1j} from predicting the level 1 slope (β_{1j}). τ_{10} is the covariance between U_{0j} and U_{1j}. The $\text{cov}(U_{0j}, U_{1j}) = \text{cov}(\beta_{0j}, \beta_{1j}) = \tau_{10}$.

Based on the equations (1) to (3), the hierarchical linear model can be expressed as:

(4) $Y_{ij} = \Upsilon_{00} + \Upsilon_{10} X_{ij} + U_{0j} + U_{1j} + \varepsilon_{ij}$

Where $\Upsilon_{00} + \Upsilon_{10} X_{ij}$ represents the fixed component and $U_{0j} + U_{1J} + \varepsilon_{ij}$, the random one. The variance of the random-effects parameters are known as variance components.

The specification of fixed and random components within the hierarchical linear model represents the major difference with the multiple regression models for each airport. The empirical model is equation (5):

(5) $\text{Block Delays}_{ij} = \beta_{0j} + \beta_{1j}\text{Enroute Miles Flown}_{ij} + \beta_{2j}\text{Speed}_{ij} + \beta_{3j}\text{NAS Delays}_{ij}$
$+ \beta_{4j}\text{Taxi-Out Delays}_{ij} + \beta_{5j}\text{Taxi-In Delays}_{ij} + \beta_{6j}\text{IMC}_{ij} + \varepsilon_{ij}$ for j airport.

FINDINGS AND INTERPRETATION

Goodness of Fit

The first step in the analysis consists in evaluating the goodness of fit of the hierarchical and multiple regression models.

In Table 2, the improvement in the -2 Log likelihood value over the iterations for each sample suggests there is "a significant improvement over the null model consisting of no random effects and a homogeneous residual error."[5]

Table 2: Fit Statistics for the Hierarchical Models

Fit Statistics			
Criteria	**Summer '07**	**Summer '12**	**Summer '13**
-2 Log Likelihood	828.0	673.9	701.3
AIC (Smaller is Better)	850.0	693.9	721.3
AICC (Smaller is Better)	851.0	694.7	722.2
BIC (Smaller is Better)	835.6	680.8	708.3

Table 3: Fit Statistics for the Multiple Regression Models

Fit Statistics			
Criteria	**Summer '07**	**Summer '12**	**Summer '13**
R^2	0.8660	0.7665	0.8408
Adjusted R^2	0.8630	0.7613	0.8373
F Value	289.63	147.16	236.83
Pr > F	<.0001	<.0001	<.0001

At a 95% confidence level, the hypothesis that any estimate in the three models equals zero can be rejected since $p < .0001$. The coefficients of determination indicate that the selected independent variables account for a large portion of the variation in block delays, albeit to a greater extent in summer 2007 and 2013 than in summer 2012. However, the multiple regression models do not specify (1) to what extent overall meteorological conditions and those at each selected airport may have accounted for any variation in block delays and (2) whether airborne delays linked to traffic management initiatives may have randomly affected block delays.

The Estimates of Fixed and Random Effects in the Hierarchical Linear Models

In Table 4, the fixed-effects estimates represent the estimated means for the random intercept and slope, respectively.

Most of the fixed effects are significant at a 95% confidence level except enroute miles flown in summer 2012 ($p > 0.05$). Taking the example of summer 2007, block delays decreased 0.0029 minutes on average for one nautical mile change in the enroute miles flown, while holding other predictors in the model constant. In summer 2012 and 2013, the sign of the estimates for enroute miles flown did not significantly change and block delays increased 0.0015 and 0.0037 minutes, respectively, for one nautical mile flown, holding other variables constant.

Although speed was significant in the three samples, its magnitude decreased after the implementation of new procedures (optimized profile descent, area navigation approaches and departures) and airspace redesign.[6] In summer 2007, block delays decreased 0.04 minutes for one nautical mile change in speed, compared with 0.0231 minutes in summer 2012 and 0.0198 minutes in summer 2013, holding other factors constant.

It is important to note that surface operation delays have the greatest impact on the variation of block delays given the magnitude of the estimates for taxi-out and taxi-in delays. In the case of the DC Metroplex, this can be explained by the lack of available gates at peak times in summer 2007 and ramp congestion prior to runway and terminal building enhancements at the three airports that were under way in summer 2012 and 2013. This explains why block delays increased 1.28 minutes on average for a one-minute change in taxi-in time in summer 2007 compared with 0.68 and 0.84 minutes, respectively, in summer 2012 and 2013, holding all factors constant. As for taxi-out operations, the implementation of tarmac delays rules[7] in April 2010 induced airlines to defer departure or cancel flight departures at times of airport congestion or poor weather conditions in order to avoid hefty penalties ($27,500 per passenger).

Table 4: Solutions for Fixed Effects

	Summer 2007					Summer 2012					Summer 2013				
Effect	**Estimate**	**Standard Error**	**DF**	**t value**	**Pr > |t|**	**Estimate**	**Standard Error**	**DF**	**t value**	**Pr > |t|**	**Estimate**	**Standard Error**	**DF**	**t value**	**Pr > |t|**
Intercept	17.2138	2.9363	274	5.86	<.0001	8.3413	1.8992	274	4.39	<.0001	4.8150	1.3960	235	3.45	0.0007
Enroute Miles Flown	-0.0029	0.0009	276	-3.33	0.001	0.0015	0.0007	38.4	1.96	0.0569	0.0037	0.0005	3.89	7.51	0.0019
Speed	-0.0403	0.0065	274	-6.16	<.0001	-0.0231	0.0043	270	-5.36	<.0001	-0.0198	0.0032	269	-6.23	<.0001
NAS Delays	0.0820	0.0064	274	12.81	<.0001	0.0388	0.0042	270	9.31	<.0001	0.0313	0.0049	275	6.43	<.0001
Taxi-Out Delays	0.1652	0.0199	274	8.29	<.0001	0.1172	0.0230	274	5.09	<.0001	0.1194	0.0195	272	6.12	<.0001
Taxi-In Delays	1.2784	0.0717	275	17.82	<.0001	0.6793	0.0691	250	9.83	<.0001	0.8380	0.8380	22.8	19.17	<.0001

Table 5: Solutions for Random Effects

	Levels		Summer 2007					Summer 2012					Summer 2013				
Effect	**apt**	**imc**	**Estimate**	**Standard Error**	**DF**	**t value**	**Pr > |t|**	**Estimate**	**Standard Error**	**DF**	**t value**	**Pr > |t|**	**Estimate**	**Standard Error**	**DF**	**t value**	**Pr > |t|**
Intercept		0	0	.	.	.	.	0	.	.	.	.	0	.	.	.	.
Airborne Delays		0	0.5319	0.06675	266	7.97	<.0001	0.7526	0.09407	10	8	<.0001	0.9826	0.06987	128	14.06	<.0001
Intercept	BWI	0	0	.	.	.	.	0	.	.	.	.	0.05113	0.07158	1	0.71	0.6052
Intercept	DCA	0	0	.	.	.	.	0	.	.	.	.	-0.0626	0.07689	1	-0.81	0.565
Intercept	IAD	0	0	.	.	.	.	0	.	.	.	.	-0.01064	0.07697	1	-0.14	0..9125
Airborne Delays	BWI	0	0	.	.	.	.	0.0669	0.0773	4.31	0.87	0.4323	0	.	.	.	.
Airborne Delays	DCA	0	0	.	.	.	.	-0.09182	0.08018	4.58	-1.15	0.3084	0	.	.	.	.
Airborne Delays	IAD	0	0	.	.	.	.	0.04451	0.0863	5.14	0.52	0.6274	0	.	.	.	.
Intercept		1	0	.	.	.	.	0	.	.	.	.	0	.	.	.	.
Airborne Delays		1	0.5324	0.05308	268	10.03	<.0001	0.7593	0.08628	7.1	8.8	<.0001	0.9226	0.05629	120	16.39	<.0001
Intercept	BWI	1	0	.	.	.	.	0	.	.	.	.	0.07898	0.07607	1	1.04	0.4881
Intercept	DCA	1	0	.	.	.	.	0	.	.	.	.	-0.02519	0.0786	1	-0.32	0.8025
Intercept	IAD	1	0	.	.	.	.	0	.	.	.	.	-0.03168	0.07747	1	-0.41	0.7529
Airborne Delays	BWI	1	0	.	.	.	.	0.163	0.07816	4.47	2.08	0.0982	0	.	.	.	.
Airborne Delays	CDA	1	0	.	.	.	.	-0.1197	0.07935	4.52	-1.51	0.1978	0	.	.	.	.
Airborne Delays	IAD	1	0	.	.	.	.	-0.02346	0.085	5.03	-0.28	0.7935	0	.	.	.	.

In Table 5, the random-effects coefficients represent the estimated deviation from the mean intercept and slope for IMC and each airport in IMC. The assumption is that airborne delays exhibit more correlation with the other factors at specific airports and meteorological conditions. According to OPSNET data, the number of traffic management initiatives (TMI) that includes miles-in-trail and minutes-in-trail, airborne holding was higher at the three airports in summer 2012 (1,267) than in summer 2007 (1,154) and summer 2013 (1,038). Minutes-in-trail describes the number of minutes while miles-in-trail describes the number of miles required between aircraft departing an airport, over a fix (a point in space that guides aircraft along a flight path), through a sector, or on a specific route. Therefore, additional spacing in time or distance was likely to have an impact of block delays, even though the enroute miles flown may have not varied drastically. That may explain why the variable "enroute miles flown" was not significant at a 95% confidence level in summer 2012.

Table 5 shows that the random effects of airborne delays are significant at a 95% confidence level whether in IMC or VMC. Regardless of the type of meteorological conditions, only the summer 2012 random-effects estimates of airborne delays at each airport were different from zero. However, the summer 2012 random-effects estimates were not significant at a 95% confidence level. It is also important to point out that the magnitude of the random-effects estimates of airborne delays in summer 2007 and 2012 were not significantly different in both meteorological conditions. In summer 2013, the magnitude of airborne delays was greater in VMC than IMC. As operations were on the rise, traffic management initiatives associated with Time-Based Flow Management between the ZDC (Washington Air Route Traffic Control Center) and adjacent centers may have increased the incidence of airborne delays to regulate the flow of traffic into the three airports.

In Table 6, the F statistic in the "Type 3 Tests of Fixed Effects" is the square of the t statistic used in the test of the independent variables. Both statistics test the null hypothesis that the slope assigned to the dependent variables equals 0.

Table 6: Type 3 Tests of Fixed Effects

	Summer 2007			Summer 2012			Summer 2013		
Effect	**Den DF**	**F Value**	**Pr > F**	**Den DF**	**F Value**	**Pr > F**	**Den DF**	**F Value**	**Pr > F**
Enroute Miles Flown	276	11.07	0.001	38.4	3.86	0.0569	3.89	56.41	0.0019
Speed	274	37.95	<.0001	270	28.74	<.0001	269	38.86	<.0001
NAS Delays	274	164.14	<.0001	270	86.61	<.0001	275	41.32	<.0001
Taxi-Out Delays	274	68.75	<.0001	274	25.94	<.0001	272	37.47	<.0001
Taxi-In Delays	275	317.52	<.0001	250	96.66	<.0001	22.8	367.56	<.0001

The slopes in Table 6 are the same as those in Table 4. The significant level ($p<0.0001$) indicates that there is evidence the slopes are not equal to zero and, therefore, significant at a 95% confidence level.

Multiple Regression Outputs

Table 7 shows the multiple regression estimates. The shaded cells highlight the factors that are not significant at a 95% confidence level. Compared with the fixed-effects estimates in Table 4, only miles flown and speed were not significant at a 95% confidence level in summer 2012 (Table 7). While IMC is significant overall during the three sampled time periods, we do not know if there is any difference by airport.

Table 7: The Multiple Regression Estimates

Variable	Summer 2007				Summer 2012				Summer 2013			
	Parameter Estimate	Standard Error	t Value	Pr > |t|	Parameter Estimate	Standard Error	t Value	Pr > |t|	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	17.5050	3.4044	5.14	0.001	2.0080	2.5373	0.79	0.4294	3.4100	1.9137	1.78	0.0759
enroute_mls_flown	0.0022	0.0008	2.84	0.0049	-0.0006	0.0005	-1.09	0.2749	0.0007	0.0005	1.42	0.1567
speed	-0.0446	0.0076	-5.88	<.0001	-0.0052	0.0057	-0.91	0.3634	-0.0108	0.0044	-2.47	0.0143
NAS_del	0.0942	0.0073	13	<.0001	0.0621	0.0053	11.74	<.0001	0.0669	0.0059	11.33	<.0001
txout_del	0.1684	0.0232	7.27	<.0001	0.1732	0.0291	5.94	<.0001	0.2526	0.0244	10.37	<.0001
txin_del	1.4436	0.0804	17.95	<.0001	0.8826	0.0733	12.04	<.0001	0.8115	0.0548	14.8	<.0001
imc	0.5466	0.1500	3.64	0.0003	0.5619	0.1246	4.51	<.0001	0.5108	0.1158	4.41	<.0001

Not significant at 95% confidence level.

FINAL REMARKS AND IMPLICATIONS

Hierarchical linear models, including fixed and random effects, can provide a better picture of performance at a construct such as the metroplex. Metroplexes play a significant role in the Next Generation Air Transportation System: They represent large metropolitan areas where the close proximity of airports is likely to create conflicting approaches and departure paths, thus reducing access potential to larger and general aviation airports. This paper used the example of the District of Columbia Metroplex where new procedures have been implemented.

At the metroplex level, enroute miles flown, speed, the number of NAS-related delays, and taxi-out and taxi-in delays have significant fixed effects on the variation of actual block times when compared with airlines' flight plans. The study indicates that instrument meteorological conditions have a significant impact overall.

As NextGen capabilities and procedures are deployed into the NAS, it will be of interest for aviation practitioners to assess whether the greater utilization of satellite navigation, as well as the implementation of performance-based navigation, will have an impact on the variation of block delays in metroplexes. While pilots' flexibility to choose trajectories and data-sharing in the cockpit are important to reduce excess miles flown, the study also suggests that attention should also be paid to surface operations' efficiency in the forms of taxi-in and taxi-out times to reduce block delays.

Endnotes

1. Created in 1935, RTCA is an organization of aviation experts and practitioners working to improve flight performance standards.

2. RTCA, NextGen Mid-Term Implementation Task Force Report, September 9, 2009, p. xiii. The document was retrieved in September 2013 at the following website: http://www.faa.gov/nextgen/media/nextgen_progress_report.pdf.

3. Multilevel analysis is also called "random coefficient model" (de Leeuw and Kreft, 1986; Longford 1993), variance component model (Longford, 1987), hierarchical linear model (Raudenbush and Bryk, 1986 and 1988), as well as mixed effects model (Littell et al. 1996). Also refer to Hox (2002:11).

4. The definitions of the causes of delay were retrieved at the website of the U.S. Department of Transportation, Bureau of Transportation Statistics, whose link is http://www.rita.dot.gov/bts/help/aviation/html/understanding.html#q4.

5. See SAS/Stats® 9.2, User's Guide, Second Edition, retrieved at http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_mixed_sect034.htm.

6. Federal Aviation Administration, NextGen Performance Snapshots, "Honoring the Past While Flying into the Future," retrieved at http://www.faa.gov/nextgen/snapshots/stories/?slide=16.

7. See 14 Code of Federal Regulation (CFR) 259.4 for the tarmac delay contingency plans.

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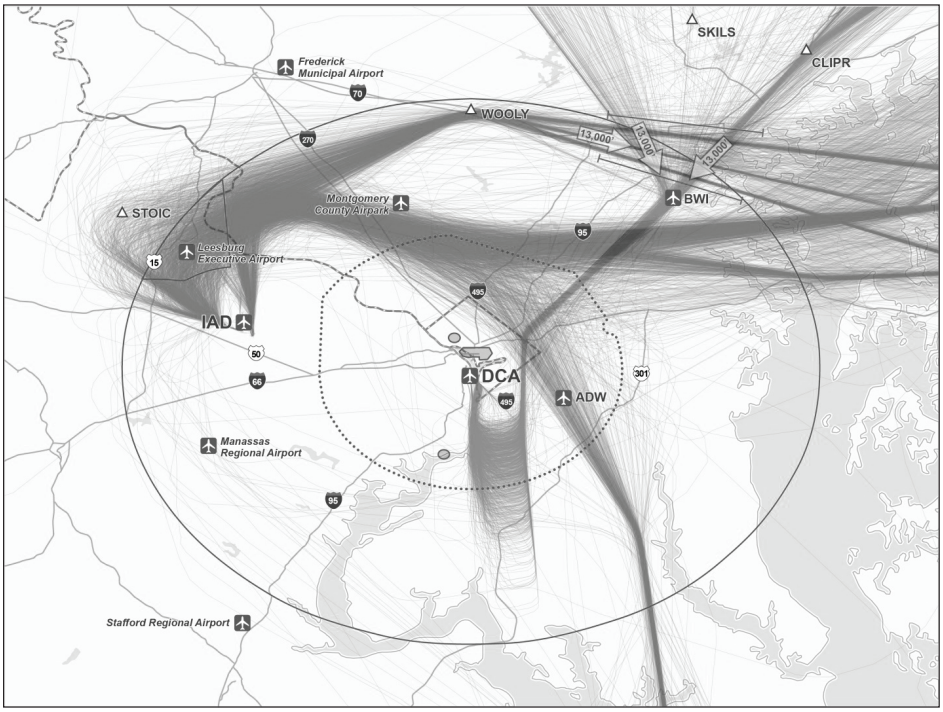
APPENDIX: Arrival and Departure Flows at the DC Metroplex



source: ATAC

ACRONYMS

AIC	Akaike Information Criterion
AICC	Akaike Information Criterion corrected for finite sample sizes
ASPM	Aviation System Performance Metrics
ATC	Air Traffic Control
BIC	Bayesian Information Criterion
BTS	Bureau of Transportation Statistics
BWI	Baltimore/Washington International Thurgood Marshall Airport
DCA	Washington Reagan National Airport
FAA	Federal Aviation Administration
IAD	Washington Dulles International Airport
IMC	Instrument Meteorological Conditions
NAS	National Airspace System
NextGen	Next Generation Air Transportation System
OPD	Optimized Profile Descent
OPSNET	Operations Network
PBN	Performance-Based Navigation
RNAV	Area Navigation
RNP	Required Navigation Procedure
RTCA	Radio Technical Commission for Aeronautics
TBFM	Time-Based Flow Management
TFMS	Traffic Flow Management System
VMC	Visual Meteorological Conditions
ZDC	Washington Air Route Traffic Control Center

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NOTE: This research does not reflect the official opinion of the Federal Aviation Administration.

Determinants of Per Capita Vehicle Miles Traveled (VMT): The Case of California

by Mintesnot Woldeamanuel and Andrew Kent

This study uses multivariate regression to isolate determinants of per capita VMT in California from the National Household Travel Survey (NHTS), as well as a Chow Test to identify structural change between the 2001 and 2009 NHTS. Results across the 2001 and 2009 NHTS data sets indicate certain determinant variables have emerged over time and others have changed in strength of impact. Our findings support mixed methods VMT reduction strategies to achieve near- and long-term GHG targets.

INTRODUCTION

Automobile travel is credited as the major contributor of greenhouse gas (GHG) emissions, accounting for about 28% of GHG emissions in the United States and 36% in California (Rodier 2009). The State of California has been a leader in climate change legislation with the passage of the Global Warming Solutions Act of 2006, AB 32, which sets GHG reduction targets to 1990 levels by the year 2020. Reducing per capita vehicle miles traveled (VMT) is one of the most effective methods for reducing GHG emissions. The relationship between GHG and per capita VMT has prompted further legislative actions and policies in California, such as SB 375, the Sustainable Communities and Climate Protection Act of 2008, which seek to reduce per capita VMT through sustainable development strategies at the regional planning level. SB 375 complements California's ambitious climate change legislation through transportation planning and sustainable development as a per capita VMT reduction strategy. As such, the relationship between GHG, per capita VMT and associated externalities requires an integrated transportation planning and environmental policy front. SB 375 directs metropolitan planning organizations (MPOs) to develop sustainable community plans which reduce GHG and links transportation funding to those strategies. The law also requires regional affordable housing shares to be developed based on local sustainable community strategies, exempts certain transit projects from environmental review, and grants the California Air Resources Board the authority to set regional GHG reduction targets.

To achieve the significant per capita VMT reduction required to meet regional and state GHG targets, sustainable community plans and state policies need to be grounded in a comprehensive understanding of California per capita VMT determinants. Previous research has made important contributions to the understanding of per capita VMT and toward crafting policy solutions. Increased access to active transportation, integrating land use with transport decisions and pricing strategies are three broad policy options for reducing automobile dependency and GHG (Bedsworth et al. 2011). Specific to California, there is a need to expand this understanding to include recent trends in per capita VMT determinants and the relative impact of determinants so state and regional planning organizations can develop effective strategies for near and long term per capita VMT and GHG reduction.

This research intends to derive a comprehensive understanding of California specific per capita VMT determinants by isolating significant VMT variables from the National Household Travel Survey for the years 2001 and 2009. Comparing significant variables between both years will grant an understanding of how determinants have changed or remained constant. Through the analysis we will also determine what kinds of variables have the greatest relative impacts on annual per capita VMT in California.

Our primary research questions include: (1) what are per capita VMT determinants in California? (2) how do per capita VMT determinants rank relatively? (3) how have per capita VMT determinants

changed over the past decade? Through answering these question we hope to recommend which per capita VMT determinants the State of California and local MPOs should concentrate on to best reduce per capita VMT and achieve California's ambitious greenhouse gas reduction targets.

LITERATURE REVIEW

Recent VMT trends indicate a moderating of national VMT growth. VMT forecasts predict a continuation of low VMT growth in the near and long term. California annual VMT growth is estimated at 1.6%, whereas, national growth is at approximately 2% (Lave 1996, Polizin et al. 2004). Some research has attributed this moderation of VMT growth to road and highway capacity reaching critical congestion levels. Research has also pointed out that while auto travel inefficiency may limit per capita VMT growth, congestion can increase GHG emissions (Barth and Boriboonsomsin 2008).

There are three basic methods of reducing vehicle emissions: (1) reduce the amount of fossil fuel consumed, (2) reduce the carbon content or output of fuel, and (3) reduce vehicle activity. Unfortunately, fuel efficiency and air quality regulation will not adequately reduce GHG emissions to achieve California's ambitious environmental objectives (Burwell 2009, Rodier 2009). Greater fuel efficiency lowers per-mile cost of driving, encouraging longer commute distances and driving more frequently (Small and Van Dender 2005). Reducing the carbon content of fuel potentially results in higher fuel prices, curbing per capita VMT; however, previous studies have found the demand for gasoline is relatively inelastic to price increases (Greene 2012). The only method which aligns state environmental and transportation planning goals are policies that directly target vehicle activity, meaning reducing vehicle driving (Litman 2013).

Related to vehicle activity, there are three components of an individual's per capita VMT contribution: (1) trip frequency, (2) trip length, and (3) mode choice (Ewing and Cervero 2007). The determinants of per capita VMT act separately on each of these components. Polizin et al. (2004) analysis showed that between 1977 and 2001, household vehicle trips increased by 115% and person miles of travel increased about 114%, demonstrating a massive climb in vehicle activity over the past few decades (Polizin et al. 2004).

Several studies have demonstrated the built environment, specifically built structures and land uses, is a major determinant of per capita VMT. For instance, one study found that highway and road lane expansion accounts for 15% of per capita VMT growth (Noland and Cowart 2000). As well, there exists strong empirical evidence that per capita VMT is negatively related to subdivision compactness and dwelling unit density (Lui 2007, Ewing and Cervero 2007, Akar and Guldmann 2012). Such research findings have prompted transit-oriented development (TOD) and smart growth policy, such as strategies supported by SB 375. The components of TOD, such as high residential density, mixed use development, traditional community design, walkability, and greater transit access, are inversely related to per capita VMT, making TODs and sustainable land use strategies a promising long-term solution.

Demographic variables have also been identified as significant determinants of per capita VMT. Variables such as population growth, age, ethnicity, immigration, income, female labor force participation, and household size all affect aggregate VMT. One study estimated up to 65% of VMT growth was potentially driven by population growth (Choi and Hu 2008). The age group with the highest VMT contribution includes young to middle age adults; therefore, the aging baby boom population is expected to have a moderating VMT growth effect as senior citizens and retired persons tend to drive less (Polizin et al. 2004). According to a Emrath and Liu (2008), households which are larger, less educated, younger, have higher incomes, have a white householder, or have a Hispanic householder are positively correlated with greater household gasoline consumption (Liu 2007). A research paper on per capita VMT determinants found that per capita VMT increases with household income, hybrid car ownership, and the number of household vehicles (Akar and Guldmann 2012).

A few California specific studies have provided valuable information on VMT determinants needed to craft policy solutions. A study comparing per capita VMT determinants across metro

regions found areas with longer commute times, younger populations, a greater number of rural inhabitants, and a greater concentration of new cars have higher rates of per capita VMT in California (Cook et al. 2012). The study also found that job density and income did not have a significant effect on per capita VMT in California, which is contrary to other research findings but may point to locational uniqueness. Another study used NPTS data from 1995 and 2001 to examine the effects of demographic composition on per capita VMT in California. The study found that demographic variables including population, age, sex, ethnicity, and immigration, significantly impact per capita VMT (Choi and Hu 2008). The statistical influence of these demographic per capita VMT determinants varied between the local and national scale. Thus, efforts to reduce per capita VMT and GHG in California will likely need to account for demographic composition over time and across space.

A principal GHG reduction strategy utilized by SB 375 and the California Air Resources Board is targeting per capita VMT through denser residential development. Alterations to land use patterns are a promising long-term strategy to promoting walking and public transit modes; however, it does not appear that increased density will be sufficient to meet California's near-term goals. Heres-Del-Valle and Niemeier (2011) found that a 10% increase in residential density would result in about a 2% decrease in per capita VMT. In the near and long term, a wide array of strategies will likely need to be implemented in California based on a larger understanding of per capita VMT determinants.

Per capita VMT reduction has been established as a necessity to resolving climate change and auto dependency (Burwell 2009, Rodier 2009). Proposed methods include land use policies, TOD, traffic calming, pricing mechanisms, transit investment, and ride-share programs. Further research on how built environment, demographics, and markets act on per capita VMT is needed to develop effective policies that serve California's climate change goals and state transportation needs.

DATA AND DESCRIPTIVE ANALYSIS

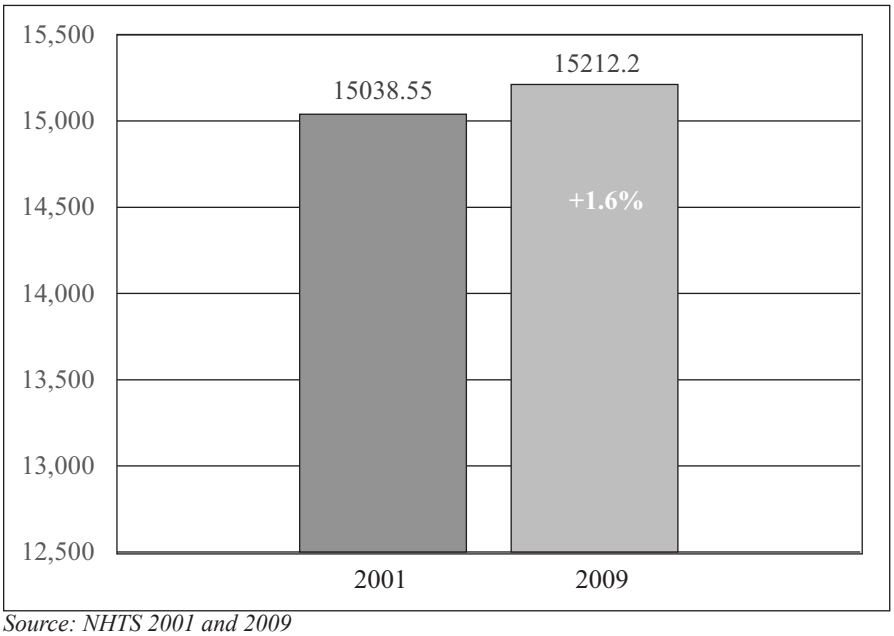
Data for isolating California per capita VMT determinants were obtained from the National Household Travel Survey (NHTS). The NHTS is a comprehensive nationwide transportation survey conducted every five to eight years by the Federal Highway Administration with the specific purpose of providing transportation researchers with data. The data were collected by the NHTS through a telephone survey using a random digit dialing system. The survey taker provided both respondent level and household level data. The NHTS data sets contain detailed information about household demographics and travel behavior. For our analysis of per capita VMT determinants and trends we used the 2001 and 2009 NHTS data sets.

Data from both years in California were systematically refined by removing households and individuals with missing and incomplete responses from the data sets. Also, numerous variables from the NHTS were initially eliminated due to an inability to compare them across the 2001 and 2009 data sets due to definition changes and uncorrectable issues. Correlation analysis was used to eliminate collinear variables.

Table 1 presents descriptive statistics of tested independent variables for the 2001 and 2009 NHTS. Figure 1 indicates California annual average per capita VMT per sampled individuals. Based on the NHTS, net VMT change in California from 2001 to 2009 is +1.6%, which is consistent with prior estimates (e.g., Lave 1996).

The descriptive statistics in Table 1 show several percent changes between the 2001 and 2009 NHTS (the last column of Table 1). For instance, the percent of families at all income levels has decreased with the exception of the highest income level, which has increased by 23%. Between 2001 and 2009, family size has decreased by 19%, from 3.05 to 2.85. The percent of homeowners has increased by 12% while the percent of renters has decreased by 13%, which seemingly indicates people converting from renting to owning a home. There is also a 7% decrease in the number of households that live in an MSA with access to rail.

Figure 1: California Average Annual VMT



Source: NHTS 2001 and 2009

For further descriptive analysis of possible per capita VMT determinants, annual per capita VMT was sorted into quartiles and graphed against variable averages within each quartile. Selected quartile graphs for the 2001 and 2009 NHTS are presented below in Figures 2 and 3. Table 2 presents the per capita VMT quartile ranges for 2001 and 2009 used in the descriptive analysis.

Table 2: Quartile Ranges for Per Capita VMT in California

Quartile	2001		2009	
	Lower Limit	Upper Limit	Lower Limit	Upper Limit
Q1	0	8000	0	10000
Q2	8001	12000	10001	12000
Q3	12001	18000	12001	18000
Q4	18001	172000	18001	137000

Source: NHTS 2001 and 2009

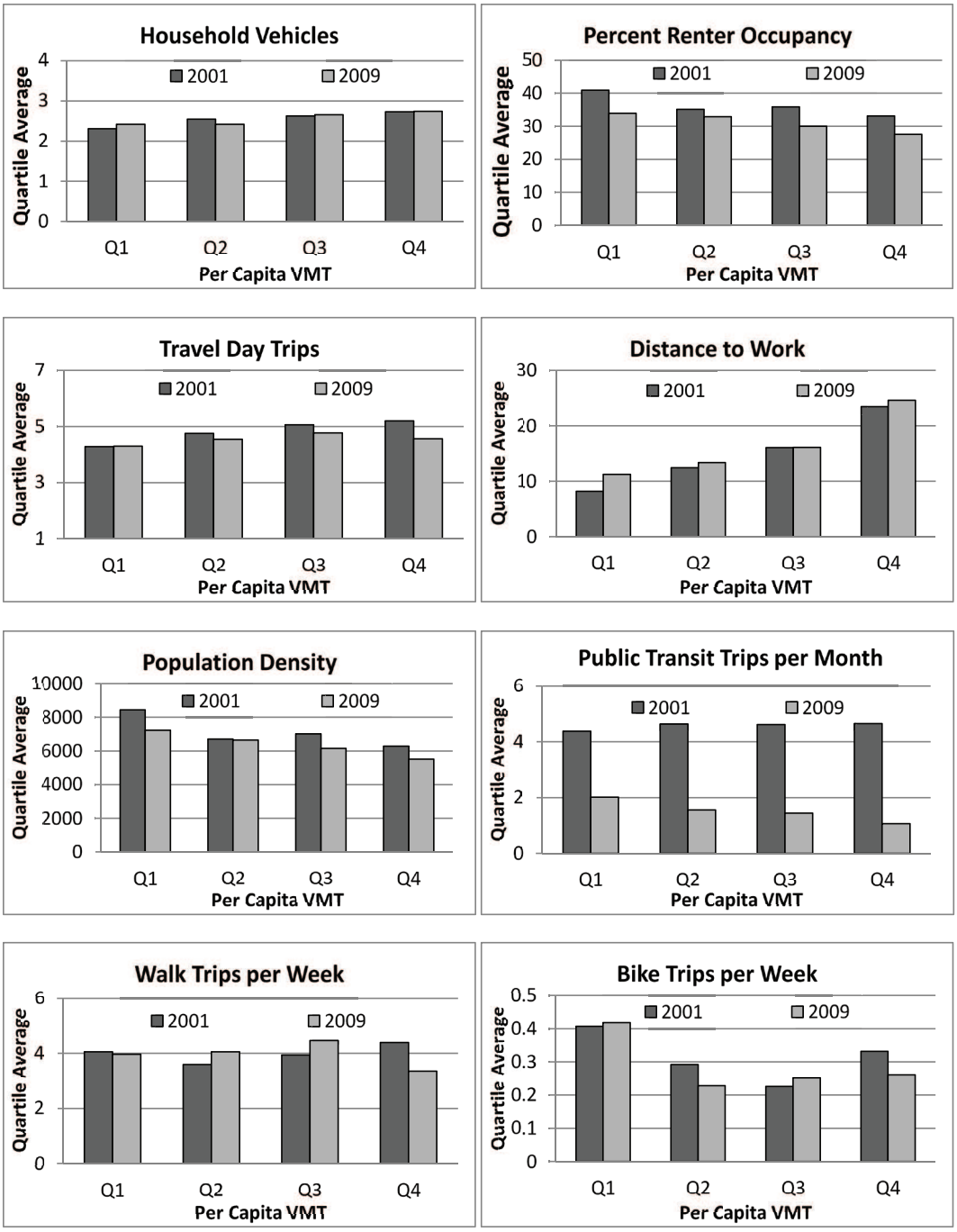
The quartile graph for the number of household vehicles by per capita VMT indicates a slight positive trend for both 2001 and 2009. The variable Percent Renter Occupancy vs. per capita VMT is distinctly a negative relationship, indicating that as renter density increases per capita VMT decreases. The opposite of Percent Renter Occupancy is Percent Owner Occupancy; therefore, homeownership and per capita VMT are positively related. Naturally, Travel Day Trips and per capita VMT are positively related. Likewise, Distance to Work and per capita VMT are positively related. Across the graphs in Figure 2 there is no visual change in per capita VMT determinants between 2001 and 2009, which indicates that for those variables, no distinct trend exists over time and there is likely stability between years.

Table 1: Descriptive Statistics of VMT Determinant Variables

Variables	Measures	2001- Tested Sample Size = 1690						2009- Tested Sample Size = 2441						Percent Change
		Min	Max	Mean	S.D.	Count	Percent	Min	Max	Mean	S.D.	Count	Percent	
% Renter Occupied- respondent's census tract	Continuous	0.00	95.00	36.00	23.00	-	-	0.00	95.00	31.00	22.00	-	-	-
Born in the U.S.	Binary	-	-	-	-	1370	81	-	-	-	-	2010	82	1
Commute Mode - Personal Vehicle	Dummy	-	-	-	-	1567	93	-	-	-	-	2303	94	2
Commute Mode - Public Transit	Dummy	-	-	-	-	50	3	-	-	-	-	59	2	-1
Distance to Work (miles)	Continuous	0.00	700.00	15.00	23.00	-	-	0.00	365.00	16.00	17.00	-	-	-
Education- Less than high school (1)	Ordinal 1-5	-	-	-	-	85	5	-	-	-	-	60	2	-3
Education- 2 - High school or GED (2)	Ordinal 1-5	-	-	-	-	350	21	-	-	-	-	295	12	-9
Education- Some college or AA (3)	Ordinal 1-5	-	-	-	-	534	32	-	-	-	-	659	27	-5
Education- Bachelor's degree (4)	Ordinal 1-5	-	-	-	-	426	25	-	-	-	-	745	31	6
Education- Graduate or Professional (5)	Ordinal 1-5	-	-	-	-	295	17	-	-	-	-	682	28	11
Family Income: 1 to 3 (< $15,000)	Ordinal 1-18	-	-	-	-	50	3	-	-	-	-	41	2	-1
Family Income: 4 to 6 (< $30,000)	Ordinal 1-18	-	-	-	-	157	9	-	-	-	-	92	4	-5
Family Income: 7 to 9 (< $45,000)	Ordinal 1-18	-	-	-	-	224	13	-	-	-	-	156	6	-7
Family Income: 10 to 12 (< $60,000)	Ordinal 1-18	-	-	-	-	245	14	-	-	-	-	226	9	-5
Family Income: 13 to 15 (< $75,000)	Ordinal 1-18	-	-	-	-	224	13	-	-	-	-	215	9	-4
Family Income: 16 to 18 (> $ 75,000)	Ordinal 1-18	-	-	-	-	790	47	-	-	-	-	1711	70	23
# of Vehicles in the Household	Continuous	0.00	9.00	3.00	1.00	-	-	0.00	11.00	3.00	1.00	-	-	-
Household Race: Asian	Dummy	-	-	-	-	141	8	-	-	-	-	195	8	-
Household Race: Black	Dummy	-	-	-	-	63	4	-	-	-	-	64	3	-1
Household Race: Multiple/Other	Dummy	-	-	-	-	192	11	-	-	-	-	84	3	-8
Household Race: Hispanic	Dummy	-	-	-	-	140	8	-	-	-	-	130	5	-3
Household Size	Continuous	1.00	10.00	3.00	1.00	-	-	1.00	11.00	3.00	1.00	-	-	-
Bike Trips (Week)	Continuous	0.00	28.00	0.00	2.00	-	-	0.00	14.00	0.00	1.00	-	-	-
Travel Day Trips	Continuous	0.00	20.00	5.00	3.00	-	-	0.00	19.00	5.00	3.00	-	-	-
Walking Trips (Week)	Continuous	0.00	75.00	4.00	6.00	-	-	0.00	99.00	4.00	6.00	-	-	-
Own a Home or Rent Apartment: Own	Dummy	-	-	-	-	1273	75	-	-	-	-	2112	87	12
Own a Home or Rent Apartment: Rent	Dummy	-	-	-	-	437	26	-	-	-	-	329	13	-13
Population Density	Continuous	50.00	30000.00	7133.00	6686.00	-	-	50.00	30000.00	6471.00	5601.00	-	-	
Public Transit Trips per Month	Ordinal 1-4	-	-	-	-	-		0.00	99.00	2.00	7.00	3868	-	-
1: 0 times	-	-	-	-	-	1456	86	-	-	-	-	-	-	-
2: 1- 4 Times	-	-	-	-	-	93	6	-	-	-	-	-	-	-
3: 5 - 10 Times	-	-	-	-	-	53	3	-	-	-	-	-	-	-
4: 11+ Times	-	-	-	-	-	88	5	-	-	-	-	-	-	-
Respondent's Age	Continuous	16.00	84.00	42.00	12.00	-	-	18.00	88.00	49.00	12.00	-	-	-
Respondent's Sex: Female	Dummy	-	-	-	-	742	44	-	-	-	-	971	40	-4
Respondent's Sex: Male	Dummy	-	-	-	-	948	56	-	-	-	-	1470	60	4
Rail (MSA has rail)	Binary	-	-	-	-	1097	65	-	-	-	-	1421	58	-7
Work: Part Time	Dummy	-	-	-	-	257	15	-	-	-	-	348	14	-1
Work: Full Time	Dummy	-	-	-	-	1426	84	-	-	-	-	2081	85	1
Work: Multiple Jobs	Dummy	-	-	-	-	7	0.00	-	-	-	-	12	0.00	-

Source: NHTS 2001 and 2009.

Figure 2: Quartile Graphs, Data from the NHTS



The quartile graph for Population Density and per capita VMT clearly indicates a negative relationship for both years. Public Transit Trips per Month versus per capita VMT indicates a slight positive relationship in 2001 and a negative relationship in 2009. This is the first graph which suggests that time has had an impact on the independent and dependent variable relationship. The graph seemingly indicates that public transit has increasing significance in reducing per capita VMT or that something over the past decade has made people more inclined to use transit over driving. Walk Trips per Week versus per capita VMT does not present a distinct relationship for 2001 or 2009. Based on the descriptive analysis, Walk Trips per Week does not seem to have any effect on per capita VMT. The graph for Bike Trips per Week presents a trend similar to an inverted bell curve, where the first two quartiles show a decreasing trend and the third and fourth quartiles seem to present an increasing trend; however, the graph is suggestive of an overall negative trend.

METHODOLOGY

Our purpose for analyzing the data sets is two-fold: isolate per capita VMT determinants from the 2001 and 2009 NHTS data sets and identify potential past trends in determinants to make policy recommendations for the future.

To identify per capita VMT determinants from the two data sets, we use multivariate regression. Regression analysis expresses an independent variable, per capita VMT, as a function of several explanatory variables. Of the possible explanatory variables in the NHTS data sets, those which are statistically significant at least at 90% confidence explain per capita VMT. To compare the relative impact of each significant variable we use the Standardized Beta Coefficient. Standardized Beta Coefficients are normalized for units so that the relative weight of each variable can be compared on a one-to-one basis. Through a direct comparison of statistically significant variables we can determine which have the greatest impact on per capita VMT.

To determine if any trends in per capita VMT determinants exist over the past decade we must first determine if regressions for 2001 and 2009 NHTS data sets differ statistically. If the regression coefficients do not differ between 2001 and 2009, then a regression model with pooled data from both years would provide per VMT determinants. To objectively determine if change has occurred in per capita VMT determinants between 2001 and 2009, we used a Chow Test.

Chow Test

The purpose of a Chow Test is to test for structural change between two regressions. A result of structural change in the regression models between 2001 and 2009 would indicate that the coefficients are significantly different. The Chow Test tests the hypothesis that the regression coefficients are different between subsets of data. In our application, we are testing if the coefficients are the same between regressions of two different years. The null hypothesis is no structural change and the alternative is structural change between subsets of data. The Chow Test requires three regressions: regressions for each data subset, and a regression with a pooled data set. The Chow Test is based on the F-distribution:

$$F = \frac{(a-b)/p}{b/(n-2p)}$$

a = Residual Sum of Squares for Pooled Model (2001 + 2009)
b = Residual Sum of Squares (2001) + Residual Sum of Squares Residuals (2009)
n = number of observations
p = number of parameters (independent variables + constant)

We use the F-distribution table to reference the critical value to determine if we reject the null hypothesis, which indicates no structural change. If structural change exists, then we can analyze separate regressions for 2001 and 2009 for trends in per capita VMT determinants using the standardized beta coefficients. If the coefficients differ between years, then we default to 2009 determinants of per capita VMT for policy recommendations. If we do not reject the null hypothesis, we can objectively say that no trends exist between years, in which case we can use regressions for either year or the regression that uses the pooled data for deriving per capita VMT determinants since there is no difference across regressions.

RESULTS

Chow Test

The F-value is F (23, 4083) = 2.75 and the critical value at .05 is equal to 1.61. Since the F-value is greater than the critical value from the F-distribution table, we rejected the null hypothesis and accepted the alternative hypothesis, which indicates structural change exists between the 2001 and 2009 data sets. Since structural change exists, the pooled data regression is not appropriate for deriving per capita VMT determinants and we must refer to the two separate regressions for 2001 and 2009. Structural change indicates that the beta coefficients are different between the 2001 and 2009 regressions. Therefore, we can analyze trends between 2001 and 2009.

Per VMT Determinant Analysis. The Chow Test revealed that the coefficients between the 2001 and 2009 data sets significantly differ. We can now use p-value and standardized beta coefficients from regression results for both years to isolate and analyze per capita VMT determinants. Table 4 presents the regression outcomes from 2001 and 2009.

Referring to Table 3, it is notable that more variables are significant in 2009 than in 2001. This indicates the emergence of a more diverse group of variables that impacts per capita VMT, and which must be accounted for when crafting strategies for reducing per capita VMT. For instance, Bike Trips per Week has emerged as a statistically significant variable in 2009. Relative to the other standardized beta coefficients, Bike Trips per Week has a moderate impact on the regression equation, indicating that the variable is an important per capita VMT determinant, although having a relatively low impact at a standardized beta of 0.05. Born in the U.S. is significant in 2009. Commute Mode – Personal Vehicle is statistically significant in both 2001 and 2009; however, there is a distinct difference in the standardized beta coefficients. In 2001, Commute Mode – Personal Vehicle has a standard beta of 0.09 and in 2009 the coefficient is at -0.05. What is notable is that the coefficient sign switches from positive to negative, indicating that commuting by personal vehicle used to have a greater impact on increasing per capita VMT than in 2009. Commute Mode – Public Transit has emerged as significant in 2009 at a standard beta at -0.08, which indicates a relatively large impact on reducing per capita VMT compared with the other variables. The emergence of commuting by public transit in recent years indicates that public transit is more relevant as a method of reducing per capita VMT.

Distance to Work is statistically significant in both years and is the most impactful explanatory variable for both years. With the greatest standardized beta coefficient of 0.22 in 2001 and 0.31 in 2009, Distance to Work must be given heavy weight by policy makers in crafting policy for reducing per capita VMT. Education emerged as a significant explanatory variable in 2009, although it has a relatively minimal impact on per capita VMT. It is interesting that Education has a negative sign, indicating that as education increases per capita VMT decreases; therefore, the least educated people tend to drive the most.

Another interesting finding is that Family Income is not statistically significant in either year, which is counter to the findings of other studies on the topic of per capita VMT. Number of Household Vehicles is significant and stable over both 2001 and 2009, with a slight change in standardized beta, falling from 0.08 to 0.06. Interestingly, Household Race-Black has emerged

in 2009 as negatively related to per capita VMT. While the impact is minimal at -0.03, this may indicate a trend toward African Americans being increasingly deprived of transportation means or even higher unemployment. Household Race – Multiple/Other has emerged in 2009 as positively related to per capita VMT at standard beta of 0.04, which is also on the low end. This category tends to contain a large portion of Hispanics and mixed race, which are both increasing in population in the United States.

Table 3: Regressions Outcomes for 2001 and 2009

Variables	2001		2009	
	Stdz. Beta	P-value	Stdz. Beta	P-value
(Constant)	-	0.09	-	0.00
Percent Renter Occupied	0.00	0.93	0.01	0.75
Bike Trips per Week	0.00	0.92	-0.07	0.00*
Born in the U.S.	0.02	0.52	0.05	0.01*
Commute Mode - Personal Vehicle	0.09	0.01*	-0.05	0.08**
Commute Mode - Public Transit	-0.05	0.18	-0.08	0.00*
Distance to Work	0.22	0.00*	0.31	0.00*
Education	-0.03	0.20	-0.03	0.10**
Household Family Income	0.00	0.99	-0.02	0.37
Household Number of Vehicles	0.08	0.00*	0.06	0.00*
Household Race- Asian	-0.04	0.14	-0.01	0.66
Household Race- Black	0.02	0.33	-0.03	0.09**
Household Race-Multiple/Other	-0.02	0.42	0.04	0.06**
Household Race- Hispanic	-0.03	0.32	0.00	0.97
Household Size	0.00	0.90	-0.02	0.51
Population Density	-0.05	0.08**	-0.09	0.00*
Public Transit Used per Month	0.01	0.65	-0.05	0.02*
Access to Rail	-0.01	0.77	-0.02	0.39
Respondents Age	-0.03	0.19	-0.09	0.00*
Respondents Sex – Male	0.17	0.00*	0.14	0.00*
Travel Day Trips	0.09	0.00*	0.04	0.05*
Walk Trips per Week	0.04	0.15	-0.02	0.35
Respondent Works Part Time	-0.07	0.01*	-0.07	0.00*
Dependent Variable : Per Capita Vehicle Miles Traveled * 95% confidence level ** 90% confidence level	R Square = 0.133 Adjusted R Square = 0.121		R Square = 0.172 Adjusted R Square = 0.165	

Our regressions support past research, which has shown population density to be a significant determinant of per capita VMT. Between 2001 and 2009, standardized beta for population density has become increasingly significant in reducing per capita VMT, with an increase from -0.05 to -0.09. Public Transit Trips per Month has become statistically significant in 2009. With a -0.05 standardized beta, trips made by public transit are moderately impactful on reducing per capita VMT. This finding is mutually supportive with Commute Mode-Public Transit, highlighting the importance of public

transit as a per capita VMT determinant. Respondent's age is a VMT determinant in 2009, and based on the beta coefficient of -0.09, the variable greatly negatively impacts per capita VMT.

The second most impactful variable in both years is Respondents Sex – Male, which is both positively related to per capita VMT. The variable Travel Day Trips are significant in both years and positively related to per capita VMT. Interestingly, standardized beta for Travel Day Trips fell from 0.09 in 2001, a strong impact, to 0.04 in 2009, which is a relatively weak impact. Finally, Respondents Part Time Worker is negatively related to per capita VMT at -0.07 in both years.

DISCUSSION AND CONCLUSION

This analysis has shown a shift toward a more diverse group of significant variables that explain and impact per capita VMT. There is also a group of variables that have remained constant over the past decade, which provides insight to which methods California and metropolitan planning organizations should concentrate their efforts toward. Particularly, variables that reduce the distance one needs to travel and the number of car trips necessary. Even across two regressions, which were proven to be statistically different, the variables Distance to work, Population Density, Travel Day Trips, and Number of Vehicles in Household proved to be consistent. Several studies have provided support for these variables as per capita VMT determinants (Lui 2007, Ewing and Cervero 2007, Akar and Guldmann 2012). This provides a measure of assurance that variables such as economic turmoil are not susceptible to change and should be a central focus of government action. These findings support the methods SB 375 used to reduce per capita VMT, which focuses on the built environment through increasing compact and mixed use development.

Over the past decade, the variables which have become relevant as VMT determinants are commuting by public transit and increasing public transit trips. The shift toward public transportation as a commute mode, as well as the relative weight of the variable, indicates a growing importance of increasing transit as a method of reducing per capita VMT. Number of bike trips has also emerged in 2009 as a per capita VMT determinant. With cycling becoming increasingly relevant, it is also an important consideration in reducing per capita VMT. These per capita VMT determinants were not particularly supported by older studies in the literature review and have been shown to have emerged here in recent years. This points to a growing importance of public transportation as part of the statewide conversation on reducing per capita VMT and by extension GHG.

Other interesting findings include the demographic variables found to be determinants of per capita VMT. The regression results for 2009 indicate that as black population increases per capita VMT decreases. This may point to a transportation equity issue and should be considered by policy makers but is outside the scope of this study. Male respondents were found to be negatively related to per capita VMT and is supported by the findings of Choi and Hu 2008. Age emerged as a statistically significant variable, negatively related to per capita VMT, in 2009, which might point to the aging of the baby boom population as supported by Polizin et al. 2004. The finding that income plays no role in determining per capita VMT was also found by Cook et al. (2012). The finding of less educated people driving more is supported by Liu (2007).

The outcomes of this study suggest to policy makers a mixed methods approach to reducing per capita VMT. This study supports efforts such as SB 375, which focuses on compact development to reduce per capita VMT and greenhouse gas emissions. This study also supports local government efforts that go further than SB 375. Reducing vehicle travel requires focusing on determinants of per capita VMT, such as increasing bike trips and public transit trips, while also decreasing distance from work to home, the number of driving trips, and the number of household cars. California's per capita VMT reduction targets can be met in the long term by focusing on these California specific per capita VMT determinants, through crafting incentives and promoting sustainable development that favors non-motorized modes.

Acknowledgements

The authors would like to acknowledge research support from Faculty Development and College of Social and Behavioral Sciences of California State University, Northridge.

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The Magnitudes of Economic and Non-Economic Factors on the Demand for U.S. Domestic Air Travel

by Ju Dong Park and Won W. Koo

The primary purpose of this study is to analyze air carriers' behavior in capturing market share by examining the economic factors affecting passenger behavior toward air travel. This study also examines non-economic factors such as seasonality, unexpected events (9/11 attack), mergers, and trends. Because the airlines included in this study compete with each other, seemingly unrelated regression estimation (SURE) is used to estimate the parameters of the demand models which have correlated error terms. The economic and statistical relationship of the factors with air passenger miles provides valuable information to understand the nature of the demand for the U.S. air passenger industry. In examining demand determinants, this study concludes that air fare, income, seasonality, and mergers play significant roles in determining the demand for air passengers.

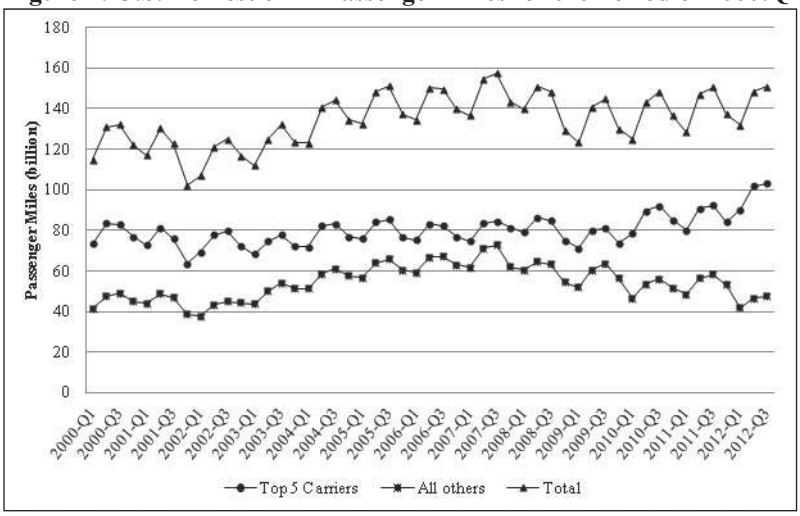
INTRODUCTION

The airline industry plays an important role in transporting people in the United States. U.S. domestic air passenger miles substantially increased from 114 billion in the first quarter of 2000 to 151 billion in the third quarter of 2012 (U.S. Bureau of Transportation Statistics 2012). With the growth of the U.S. airline industry, competition among airlines and its impacts on passenger travel have become the prevailing issue in air transportation economics since the Airline Deregulation Act of 1978,which undoubtedly, was the most important event affecting the airline industry. It partially shifted control for air travel from the political platform to the marketplace. Competition among major airlines under deregulation brought some benefits, such as air fare reductions, and improvements in capacity utilization for the U.S. airline industry. As shown in Figure 1, the total U.S. domestic airline passenger miles increased by 31% while passenger miles for the top five U.S. carriers[1] increased by 41% during the period of 2000:Q1-2012:Q3.

Figure 2 shows the U.S. nominal and real average air fares per passenger mile for the period of 2000:Q1-2012:Q3. The nominal average air fare in the United States increased by three cents (2000 U.S. dollar) for the 12 years; however, the real average air fares per passenger mile decreased by two cents for the same period. In general, U.S. domestic air fares decreased from 2000 to 2012, resulting in an increase in U.S. domestic air travel.

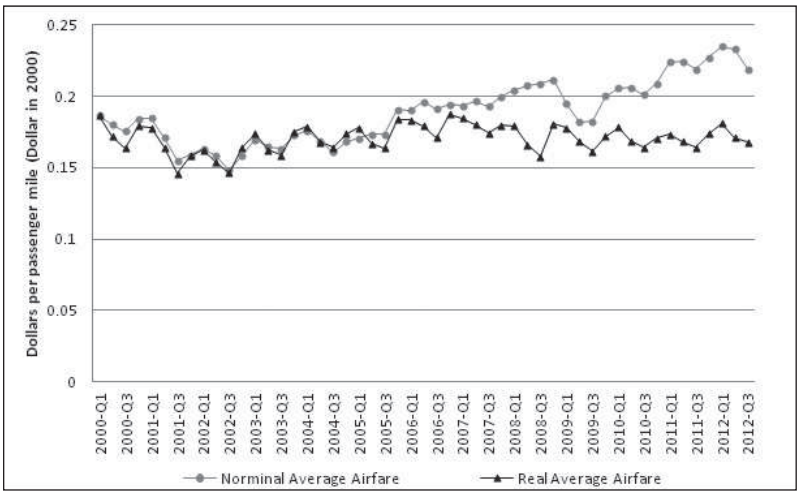
The primary purpose of this study is to analyze air carriers' behavior in capturing market share by examining the economic factors and non-economic factors that affect passenger behavior toward air travel in the United States. Some of the factors are air fare, disposable income, seasonality, the 9/11 attack, and mergers.

Figure 1: U.S. Domestic Air Passenger Miles for the Period of 2000:Q1-2012:Q3



Source: The T-1 tables, Bureau of Transportation Statistics, 2012.

Figure 2: U.S. Nominal and Real Average Air Fares per Passenger Mile for the Period of 2000:Q1-2012:Q3



Source: T-1 tables, Bureau of Transportation Statistics, 2012.

LITERATURE REVIEW

Many studies have investigated the effects of demand for air passenger services using various methods. Proussaloglou and Koppelman (1995) investigated carrier demand in a competitive context and analyzed air carrier choice to assess the market share and revenue implications of service design, pricing, marketing, and promotional strategies. Later, Proussaloglou and Koppelman (1999) extended the conceptual framework and applied it to the choice of carrier, flight, and fare class as a basis for analyzing air travel demand in a competitive market. Brons, Pels, Nijkamp, and Rietveld (2002) used meta-regression analysis to investigate the determinants of price elasticity for inter-continental and international airline services and to identify both common and contrasting factors that influence price elasticity.

Njegovan (2006) examined outbound demand for leisure air travel in the United Kingdom using a demand system that takes into account the ways in which the expenditure on air fares interacts with both the expenditure on non-fare components[2] of travel abroad and with expenditure on domestic leisure. He used the Almost Ideal Demand System (AIDS) models and found that there are strong interactions between air-travel expenditures, other costs of travel abroad, and expenditures on leisure activities in the United Kingdom.

More recently, Chi and Baek (2012) studied short- and long-term effects of determinants of the demand for U.S. air passengers. The authors used the Johansen co-integration analysis and a vector error-correction (VEC) model. NASDAQ (National Association of Securities Dealers Automated Quotations) was used as a proxy for measuring business travel while U.S. disposable income was used as a proxy for measuring leisure passengers. Chi and Baek (2012) found that air fare, disposable income, and NASDAQ had significant effects on U.S. air passenger demand in the long run while the combined short-run dynamic effects of disposable income, NASDAQ, population, and air fare explained changes in air passenger miles.

Nelson, Dickey, and Smith (2011) analyzed the factors affecting the number of visitors to Hawaii from the U.S. mainland. The authors used a double-log form for the airline-demand model and found that cross sectional (spatial) air fare elasticities, on an annual basis, were high and growing over time, but the results estimated from the time series analysis (temporal) were much lower.

However, studies in this field have paid little attention to the empirical analysis of passenger demand for air travel in the United States. In this study, an econometric model is developed to estimate price elasticity, cross-price elasticity, and income elasticity of the demand for U.S. domestic air passengers. Only the top five U.S. carriers are used for this study because their average market share from 2000 to 2012 is 59.84% of the entire market (U.S. Bureau of Transportation Statistics 2012). Based on our empirical analysis, we evaluate domestic air passengers' behavior among the top five carriers, examining the impact of economic and non-economic variables.

CHARACTERISTICS OF THE U.S. AIRLINE INDUSTRY

In 1978, the Airline Deregulation Act was passed to remove government control over the pricing of airline services, operating service routes, market entry and exit, as well as inter-carrier agreements and mergers. Under the Civil Aeronautics Board (CAB) regulation, air carriers' investments and operating decisions were highly restricted. With the CAB controlling the operating routes, market entry/exit, and air fare, the airlines were limited to competing only on food, cabin crew quality, and flight frequency. As a result, air fares and flight frequency were high while load factors[3] were low. Since the deregulation in 1978, the air-transportation market has changed significantly. Airline companies can now control air fares, operating routes, and flight frequency. Therefore, flight frequency is much lower with higher load factors than before deregulation. Borenstein and Rose (2007) found that the average load factors for domestic scheduled service climbed from lows of under 50% prior to deregulation, to over 60% in the mid-1980s, remaining above 70% since the late 1990s and hitting 83% in 2011. Although the U.S. airline industry was deregulated under the 1978 Airline Deregulation Act, the industry's infrastructure, such as regulation of airport facilities, still remains subject to government control.

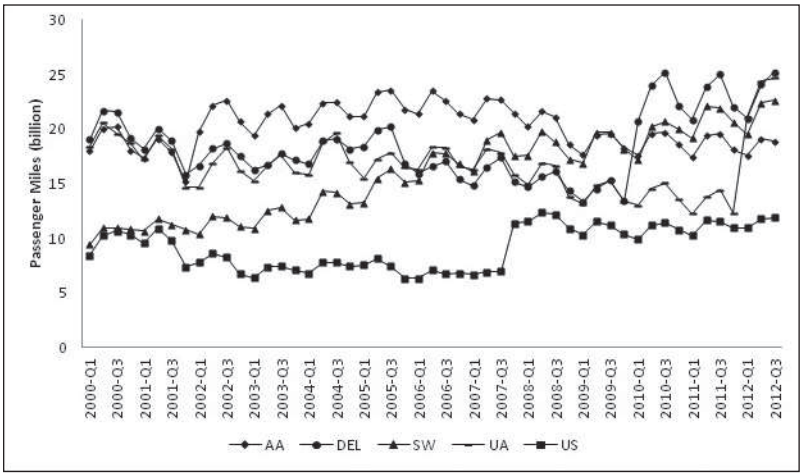
Under deregulation of the airline industry, the number of passengers at major hub airports grew; therefore, airline companies attempted to capture more passengers using various methods. One such alternative is low-fare, no frills,[4] and point-to-point service. For instance, Southwest Airlines began offerings its then unique short haul, no frills, low priced, and interstate service. During the 1990s, Southwest moved into the ranks of the nation's top 10 airlines. Most recently, several major airlines, including Continental, Delta, United, and US Airways, have created subsidiaries that offer low-fare, low-frill, and point-to-point services using economy-sized aircraft.

Nonstop services for U.S. domestic air travel began to increase in the late 1990s. This change corresponded to the widespread introduction of regional jets (RJs), jet aircraft with capacities of fewer than 100 seats that are more efficient than propeller aircraft and/or larger jets. For medium length routes, RJs' low seat-mile costs were capable of supporting airline service in small cities. The ability to serve such markets economically with small jet airliners created the possibility of adding smaller cities and more frequent services to the spokes airports from the hubs, and it also created point-to-point services in the marketplace. Thus, the recent trend in the airline industry is an increase in small jet aircraft service while either maintaining or reducing large jet aircraft service.

Figure 3 shows the passenger miles among the major U.S. air carriers for passenger travel during the period of 2000:Q1-2012:Q3. American Airlines increased its passenger miles by 5%, Delta Airlines by 32%, Southwest Airlines by 140%, United Airlines by 34%, and US Airways by 41%. However, extraordinary decreases in passenger miles for the five major air carriers occurred in the fourth quarter of 2001, immediately after the September 11 attacks.

US Airways increased its market share during the fourth quarter of 2007 through the first quarter of 2008 as the result of a merger with America West at the end of 2005. In the middle of 2008, Delta Airlines and Northwest Airlines agreed to merge, resulting in increased passenger miles for Delta Airlines from the fourth quarter of 2009 to the first quarter of 2010. A merger of United Airlines and Continental Airlines in 2010 brought an improvement in passenger miles from the fourth quarter of 2011 to the first quarter of 2012. These three mergers significantly affected the domestic airline market for passenger services.

Figure 3: Domestic Air Passenger Miles of the Top Five U.S. Carriers for the Period of 2000:Q1-2012:Q3



Source: The T-1 tables, Bureau of Transportation Statistics, 2012.

In addition, alliances between airlines vary from a limited marketing arrangement, such as sharing frequent-flyer programs, to more complex agreements, such as code-sharing. Code-sharing forms the basis of most airline alliances and allows airlines to sell seats on partners' flights as if these flights were their own. Firms use code-sharing agreements for different reasons, such as indirect entry into markets where costs and regulatory barriers would make direct entry impossible, the expansion of networks, and increasing service quality.

Code-sharing agreements operate under either the blocked-space system or the free-sale system. With the blocked-space system, aircraft capacity is shared between marketing carriers[5] and the operating carrier.[5] The marketing carrier buys a block of seats from the operating carrier, sells them to its passengers as its own seats, and keeps all the revenue from those sales. The operating

carrier cannot sell any of the seats assigned by the marketing carrier, and both carriers charge fares independently. With the free-sale model, all partners have free, real-time access to the operating carrier's seats, and there is no fixed limit on how many seats the marketing carriers can sell. Moreover, the marketing carrier determines its fares independently from the operating carrier. All revenue from seats that the marketing carrier sells under the free-sale system is kept by the operating carrier.

For example, suppose a passenger buys an indirect ticket from A to C through B from American Airlines, where the flight from A to B is operated by American Airlines and the flight between B and C is operated by US Airways. Under a code-sharing agreement and a free-sale system between them, American Airlines would keep all the revenue generated from the A to B flight and US Airways would keep all the revenue generated from the B to C flight. If there is not a code-sharing agreement between American Airlines and US Airways, a passenger who is looking for a flight from A to C will not buy his/her ticket from American Airlines because it does not offer the service from A to C. As a result, the passenger will buy his/her ticket from another carrier, and American Airlines will lose this passenger. Therefore, it is preferable for American Airlines to accept the code-sharing agreement to earn positive revenue from A to B, rather than losing passengers. Because it is hard to clarify the measurement of revenue passenger miles and the total revenue for air carriers during a certain time period in a given dataset from the U.S. Department of Transportation, concerns about code-sharing effects on air passenger miles and air fares are ignored in this study.

As mentioned previously, there have been four major mergers among U.S. domestic airlines in the last 12 years. Many policy makers are concerned that mergers would substantially reduce competition, increase air fares, and cut service while airline companies say that a merger would reduce their operating costs and allow them to offer lower prices and better service. Airline mergers create advantages and disadvantages for air passengers. On the down side, the merger would lead to a consolidation of routes, giving an airline a monopoly over a particular route, which might cause the fare to increase. However, the merger can open an entry for another airline to operate service in the market and to start charging less. Table 1 shows U.S. airline mergers and acquisitions since 2000. There were a total of 12 mergers among U.S. airline companies in the last 13 years. This study includes the mergers of US Airways with America West Airlines (2005), Delta Airlines with Northwest Airlines (2009), and United Airlines with Continental Airlines (2010). The merger between American Airlines and US Airways is not included in this study mainly because the merger occurred in 2013, which is the last observation included in this study.

Table 1: U.S. Airline Mergers and Acquisitions

Date		Air Carrier	Resulting Entity
Announced	Closed		
01/10/2001	04/09/2001	American Airlines / TWA	American Airlines
04/22/2005	05/09/2011	Republic Airways / Shuttle America	Republic Airways
05/19/2005	09/27/2005	US Airways / America West Airlines	US Airways
08/15/2005	09/08/2005	SkyWest / Atlantic Southeast Airlines	SkyWest / ASA
01/18/2007	01/18/2007	Pinnacle Airlines / Colgan Air	Pinnacle Airlines / Colgan Air
11/19/2008		Southwest Airlines / ATA Airlines	Southwest Airlines
04/14/2008	12/31/2009	Delta Airlines / Northwest Airlines	Delta Airlines
06/23/2009	07/31/2009	Republic Airways / Midwest Airlines	Republic Airways
08/14/2009	10/01/2009	Republic Airways / Frontier Airlines	Republic Airways
05/03/2010	10/01/2010	United Airlines / Continental Airlines	United Airlines
08/04/2010	11/15/2010	SkyWest / Atlantic Southeast Airlines / ExpressJet Airlines	SkyWest / SureJet
09/27/2010	05/02/2011	Southwest Airlines / AirTran Airways	Southwest Airlines
07/01/2010	07/01/2010	Pinnacle Airlines / Mesaba Airlines	Pinnacle Airlines / Mesaba Airlines
02/14/2013	12/09/2013	US Airways / AMR / American Airlines	American Airlines (AAL)

Source: Airlines for America.

THE MODEL

This study developed a theoretical model of demand for air passenger services through maximizing passengers' utility under a given budget constraint. Following McCarthy (2001), the utility function for the air transportation passengers and their budget constraint are specified as follows:

(1) $Max\ U = f_u(PM^1, PM^2, \dots, PM^i)$

individual's budget constraint is

(2) $\sum_{i=1}^{n} AF^i \cdot PM^i = INC$

where PM^i is total passenger miles of the airline company i (i=1,2,…,n); AF^i is air fare per passenger mile of the air carrier i (i=1,2,…,n); and INC is individual's budget allocated for air travel.

The Lagrangian equation is formed from equations (1) and (2) as follows:

(3) $\mathrm{L} = f_u(PM^1, PM^2, \dots, PM^i) + \lambda\,(INC - \sum_{i=1}^{n} AF^i \cdot PM^i)$

The first differential of equation (3) with respect to PM^i and λ yield

(4) $\frac{\partial L}{\partial PM^i} = f_u^i - \lambda AF^i$ for $i = 1,2, \dots, n$

(5) $\frac{\partial L}{\partial \lambda} = INC - \sum_{i=1}^{n} AF^i \cdot PM^i$

where $f_u^i = \frac{\partial f_U}{\partial PM^i}$ for $i = 1,2,\dots,n$

Equating equations (4) and (5) to zero and solving yield demand for air travel as:

(6) $PM^i = f_D(AF^1, AF^2, \ldots, AF^n, INC)$

Based on equation (6), we specified an empirical demand model of each airline. Airlines considered in this study are American Airlines, Delta Airlines, Southwest Airlines, United Airlines, and US Airways. In addition, the demand model includes non-economic variables representing seasonality for passengers' preference of season for their air travel. Another additional non-economic variable included in the model is the September 11 terrorist attacks to examine whether the attack affects air travel. We also added dummy variables representing mergers between US Airways and America West Airlines in 2005, Delta Airlines and Northwest Airlines in 2009, and United Airlines and Continental Airlines in 2010. The empirical model also includes the trend variable to examine whether there is a general trend in passengers' air travel in the U.S. The empirical model is specified as:

(7) $PM_t^i = f(AF_t^1, AF_t^2, AF_t^3, AF_t^4, AF_t^5, INC_t, SE, SEP\_ATT, MER)$

where PM_t^i is the total passenger–miles of U.S. domestic carrier *i* at time period *t*; AF_t^i is the air fare per passenger mile of carrier *i* at time period *t*; INC_t is the disposable income per capita; *SE* is a dummy variable representing the seasonal effects; *SEP_ATT* is a dummy variable representing the impact of the September 11 attack; *MER* is a dummy variable representing the impact of mergers among airline companies. Equation (7) is re-specified under a double log functional form as:

(8) $\ln PM_t^i = \alpha_i + \sum_{j=1}^{5} \beta_{ij} \ln AF_t^j + \gamma_i \ln INC_t + \sum_{h=1}^{3} \delta_{ih} D_t^h + \delta_i^{sa} D_t^{sa} + \sum_{k=1}^{3} \delta_k D_t^k + \tau_i lnTRE + \varepsilon_{it}$

where α is the intercept term and the βs,γs, δs, and τs are coefficients of corresponding variables. $\ln PM_t^i$ is log value of the total air passenger miles (billions) of carrier *i* in time *t*, $\ln AF_t^j$ is log value of average air fare per mile (U.S. dollar) of carrier *j* in time *t*, $\ln INC_t$ is log value of average per capita disposable income (thousands of U.S. dollars) in time *t*. In addition, D_t^hs are seasonal dummy variables for Spring (D_t^1), Summer (D_t^2), and Fall (D_t^3), D_t^{sa} is a dummy variable representing the September 11 attack, and D_t^ks are dummy variables for mergers of US Airways (D_t^1), Delta Airlines (D_t^2), and United Airlines (D_t^3). Finally, *TRE* represents trend variable and ε_{it} is the random error terms.

The estimated coefficient (β_{ij}) represents own and cross price elasticites. It is expected $\beta_{ij} < 0$ for $i=j$ and $\beta_{ij} < 0$ or $\beta_{ij} > 0$ for $i \neq j$, depending upon the relationship between the airlines. If two airlines are substitutes for each other, $\beta_{ij} > 0$ for $i \neq j$ and $\beta_{ij} < 0$ for $i \neq j$ if the airlines are complements. The estimated coefficient (γ_i) represents income elasticity and is expected to be positive. The coefficient (δ_{ih}) represent seasonal effects and the sign is expected to be either positive or negative, depending upon passengers' preference of seasons for their travel. The estimated coefficient (δ_i^{sa}) represents the September 11 terrorist attack and the sign of the coefficient is expected to be negative mainly because of passengers' hesitation to fly for the short period just after the attack. The coefficient (δ_k) represents the effects of the airline merger, and the signs are expected to be positive. Finally, τ_i represents the general trend of passenger travel by air, and the sign is expected to be either positive or negative.

DATA

To analyze the effects of economic factors and non-economic factors on major air carriers' passenger miles in U.S. domestic air transportation service, time-series data for passenger miles and air fare per passenger mile are collected for the following major U.S. carriers: American Airlines (AA), Delta Airlines (DEL), Southwest Airlines (SW), United Airlines (UA), and US Airways (US). Quarterly data for 2000:Q1 through 2012:Q3 were used for this study.

The total air passenger miles are used as a proxy for air passenger demand and are collected from T-1 tables published by the Bureau of Transportation Statistics (BTS) in the U.S. Department of Transportation (USDOT). The tables (T-1) summarize the T-100 traffic data reported by air carriers. The monthly data compiled by U.S. air carriers include available seat miles (ASMs), available ton miles (ATMs), revenue passenger miles (RPMs), revenue ton miles (RTMs), revenue air hours (RAHs), revenue miles flown (MILES), and revenue departure performed (FLIGHTS). Because quarterly data were used for this study, quarterly RPMs are calculated by summing monthly data.

The average air fare per passenger mile is used as a proxy for air fare and is obtained from F41 tables published by the BTS in the USDOT. The F41 tables contain financial information on large certified U.S. air carriers and include balance sheets, cash flow, employment, income statements, fuel cost and consumption, and aircraft operating expenses. Large certified carrier means the air carrier that holds the Certificate of Public Convenience and Necessity issued by the USDOT with annual operating revenues of $20 million or more. Since F41 tables provide quarterly data for operating revenues by airlines, an average air fare per passenger mile for U.S. domestic air passenger service of each air carrier was calculated by dividing total operating revenues by total RPMs as a proxy of average air fares by each airline. Since this study focuses on aggregate demand for air travel in the United States, the price variables (average air fare per passenger mile) by airlines are the most appropriate in estimating the price effect on aggregate demand for air travel by airlines.[7] Stratifying the data by flight length will provide the relationship between air fare and distance; however, this study is not focused on this issue.

The U.S. personal disposable income per capita is from the B-30 table, U.S. Government Printing Office (2012). Table B-30 provides quarterly data for disposable personal income. The Consumer Price Index (CPI) for air fare and the general CPI were used separately to calculate the real value for air fare and disposable personal income. Both the general CPI and CPI for air fare were obtained from the Bureau of Labor Statistics (BLS), United States Department of Labor (2012). The data used for empirical analysis contain 51 quarterly observations.

Summary statistics for the dataset are presented in Table 2. This study includes only the top five airline companies in the United States for the period of 2000:Q1 to 2012:Q3 mainly because more than 50% of total market share is accounted for those five airline companies (Bureau of Transportation Statistics 2012). In Table 2, average air fare per mile is measured in U.S. dollars adjusted by the CPI for air fare and average per capita income is measured in thousands of U.S. dollars and adjusted by CPI.

Table 2: Summary Statistics

Airlines		Variable		
		PM_t^i	AF_t^i	INC_t
American Airlines	Max	236	0.167	
	Min	150	0.122	
	Mean	202	0.145	
	s.d	19.26	0.022	
Delta Airlines	Max	252	0.204	
	Min	134	0.123	Max: 37.925
	Mean	185	0.173	
	s.d	31.44	0.031	
Southwest Airlines	Max	226	0.149	Min: 25.094
	Min	95	0.112	
	Mean	158	0.125	
	s.d	39.02	0.024	Mean: 31.094
United Airlines	Max	246	0.191	
	Min	123	0.125	
	Mean	167	0.164	s.d: 4.234
	s.d	26.37	0.027	
US Airways	Max	124	0.230	
	Min	63	0.158	
	Mean	92	0.191	
	s.d	19.84	0.033	

Data sources: U.S. Department of Transportation, U.S. Government Printing Office, and U.S. Department of Labor.
Standard Deviation is abbreviated as s.d. in the table.
Total air passenger miles (billions) of carrier *i* in time period *t* is abbreviated as PM_t^i in the table.
Average air fare per mile (US dollars) of carrier *i* in time period *t* is abbreviated as AF_t^i in the table.
Average per capita disposable income (thousands of US dollars) in time period *t* is abbreviated as INC_t in the table.

ECONOMETRIC PROCEDURE AND EMPIRICAL RESULTS

Autocorrelation was tested by using the Durbin-Watson (DW) statistics. If autocorrelation is present, the Ordinary Least Squares (OLS) is no longer the Best Linear Unbiased Estimator (BLUE) (Stock and Watson 2010). The DW tests for AA, DEL, and SW under the double-log model indicates that the test is inconclusive because the values of the DW test were between 1.039 (critical value of lower bound) and 1.748 (critical value of upper bound) at the 1% significant level. The DW statistics for UA and US are close to 2, which accepts the null hypothesis of no serial correlation. To correct for the presence of first-order serial correlation for AA, DEL, and SW, the Yule-Walker (YW) method was applied. After serial correlation correction, all variables of the DW test were close to 2, indicating that the null hypothesis of no serial correlation is accepted.

The *F-test* is used to test a joint hypothesis for seasonality. For the test, we developed two models: an unrestricted model including seasonal dummy variables and a restricted model excluding seasonal dummy variables. The null hypothesis is $H_0: \delta_{i1} = \delta_{i2} = \delta_{i3} = 0$ and the alternative hypothesis is $H_a: \delta_{i1} \neq \delta_{i2} \neq \delta_{i3} \neq 0$. If H_0 is rejected, there is seasonality in the industry. The test statistics are calculated as follows:

(9) $$F_{q,n-k} \sim \frac{(SSE_R - SSE_{UR})/q}{SSE_{UR}/n-k}$$

where *SSE* is the sum of squared errors. The subscript represents type of model; *UR* represents unrestricted model and *R* represents restricted model.

Table 3 shows the result of the *F-tests* for seasonality for each airline. The null hypothesis of no seasonality for all five air carriers are rejected since the values of the *F-test* for seasonality are 13.219 (AA), 9.742 (DEL), 98.420 (SW), 26.132 (UA), and 6.928 (US), respectively. Since all values of *F-test* for seasonality are greater than the critical value of $F_{(3,40)}$(=4.31) at the 1% significant level, it is concluded that there is seasonality of demand for domestic air passengers, especially for those five major airlines in the United States.

Table 3: Result of F-test for Seasonality

Air Carrier	*Sum of Square Error (SSE)*		*F-test*
	Unrestricted Model	Restricted Model	
American Airlines (AA)	0.0416	0.0839	13.219***
Delta Airlines (DEL)	0.1901	0.3363	9.742***
Southwest Airlines (SW)	0.0226	0.1937	98.420***
United Airlines (UA)	0.2014	0.6169	26.132***
US Airways (US)	0.1929	0.2984	6.928***

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

The *t-test* was used to examine the effects of the terrorist attack on September 11 and each merger. To test effect of the September 11 attack, the null hypothesis is $H_0: \delta_i^{sa} = 0$; and the alternative hypothesis is $H_a: \delta_i^{sa} \neq 0$. If H_0 is rejected, there is an impact of the attack on the industry; otherwise, there is no impact of the attack on the industry. Likewise, the *t-test* was used to test the effect of each merger on the U.S. domestic airline industry. The null hypothesis is $H_0{:}\delta_1 = 0$ for US Airways's merger and the alternative hypothesis is $H_a{:}\delta_1 \neq 0$. For the Delta Airlines's merger, the null hypothesis is $H_0{:}\delta_2 = 0$ and the alternative hypothesis is $H_a{:}\delta_2 \neq 0$. Lastly, for the United Airlines's merger, the null hypothesis is $H_0{:}\delta_3 = 0$ and the alternative hypothesis is $H_a{:}\delta_3 \neq 0$. If H_0 is rejected, there is an impact of mergers on the industry; otherwise, there is no impact of mergers on the industry.

Since the airlines included in this study compete with each other, Seemingly Unrelated Regression Estimation (SURE) by Zellner (1962) is used to estimate the parameters of the demand models under an assumption that individual demand models are correlated through error terms. In other words, if the residuals of individual demand equations are correlated with one another, SURE is more efficient than single equation estimation (Pindyck and Rubinfeld 1998).

Table 4 shows the results of SURE of the demand for U.S. domestic air travel. The *system* R^2 is 0.9746, indicating that the independent variables in the model explains 97% of the variation of the dependent variables.

In the demand model for air passengers of American Airlines, own price elasticity of demand is -0.909 and statistically significant at the 1% significant level, indicating that AA's passenger miles increases by 0.909% when its air fare per passenger mile decreases by 1%. Its cross price elasticity with Delta Airlines, Southwest Airlines, and United Airlines are 0.149, -0.009, and 0.057 and they are not statistically significant; however, its cross price elasticity of demand for US Airways is 0.543 and statistically significant at the 1% significant level. This indicates that these two airlines

Table 4: Result of Seemingly Unrelated Regression Estimation (SURE)

Variable	AA	DEL	SW	UA	US
Intercept	5.531 (1.27)	14.42 (1.65)	3.954 (1.43)	2.074 (0.30)	11.923* (1.76)
LNAFAA	-0.909*** (-2.77)	0.770 (1.28)	0.414* (1.99)	0.684 (1.29)	1.406*** (2.77)
LNAFDEL	0.149 (0.66)	-1.06** (-2.51)	-0.146 (-1.01)	-0.415 (-1.14)	-0.444 (-1.27)
LNAFSW	-0.009 (-0.04)	0.264 (0.72)	-0.45*** (-3.53)	1.089*** (3.33)	0.3996 (1.29)
LNAFUA	0.057 (0.39)	0.127 (0.46)	0.215** (2.28)	-0.298 (-1.23)	0.210 (0.91)
LNAFUS	0.543*** (3.47)	0.558** (1.95)	0.273** (2.75)	0.640** (2.56)	-1.893*** (-6.63)
LNINC	1.294** (2.51)	0.404 (0.39)	1.505*** (4.60)	2.131** (2.59)	0.495 (0.62)
D1	0.012 (0.58)	0.009 (0.25)	-0.09*** (-6.32)	0.394 (1.16)	-0.036 (-1.08)
D2	0.083*** (3.96)	0.142*** (3.62)	0.089*** (6.67)	0.232*** (6.98)	0.088*** (2.69)
D3	0.100*** (4.27)	0.182*** (4.11)	0.098*** (6.61)	0.312*** (8.35)	-0.027 (-0.72)
D4	-0.209*** (-4.99)	-0.068 (-0.87)	-0.002 (-0.09)	0.054 (0.81)	-0.086 (-1.32)
D5					0.241*** (4.98)
D6		0.320*** (5.80)			
D7				0.262*** (5.19)	
TRE	-0.029*** (-2.77)	0.008 (0.38)	0.041*** (7.21)	-0.04*** (-2.49)	-0.030** (-2.15)
System R^2	0.9746				
df[a]	192				

Degree of Freedom is abbreviated as *df* in the table.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

compete with each other in most routes. Income elasticity of demand for American Airlines is 1.294 and is statistically significant at the 5% significant level. If per capita income increases by 1%, AA's passenger miles increase 1.294%. Since the estimated coefficients of seasonal dummy variables for summer and fall are 0.083 and 0.100 and statistically significant at the 1% significant level, AA's passenger miles increase by 0.083% and 0.100% during summer and fall, respectively. However, the estimated coefficient of seasonal dummy variable for spring is 0.012 and insignificant. The estimated coefficient of the dummy variable for the September 11 attack is -0.209 and statistically significant at the 1% significant level, indicating AA's passenger miles decreased by 0.209% as a result of the September 11 attack. Lastly, the estimated coefficient of trend variable is -0.029 and is statistically significant at the 1% significant level.

In column (3), Delta Airlines's own price elasticity of demand is -1.06 and statistically significant at the 5% significant level. This implies that passenger miles of DEL decrease by 1.06% for every 1% increase in its air fare per passenger mile. Its cross price elasticity with US Airways is 0.558 and statistically significant at the 5% significant level, indicating that they compete with each other in most routes. The cross price elasticities of American Airlines, Southwest Airlines, and United Airlines are 0.770, 0.264, and 0.127, respectively, but are not statistically significant. Income elasticity of demand is 0.404 but insignificant for Delta Airlines. This might be interpreted that Delta Airlines is likely to have more business travel passengers than leisure travel passengers. In general, leisure travel passengers are more sensitive to air fare than business travel passengers. The estimated coefficient of seasonal dummy variable for summer and fall are 0.142 and 0.182 and statistically significant at the 1% significant level while spring is 0.009 but insignificant. DEL's passenger miles increase by 0.142% and 0.182% during summer and fall, respectively, and are significant at the 1% level. The estimated coefficient of the dummy variable for the September 11 attack is -0.068, but insignificant, which means DEL's passenger miles may not have been affected by the September 11 attack. The estimated coefficient for mergers between Delta Airlines and Northwest Airlines is 0.320 and statistically significant at the 1% significant level, indicating that passenger miles of Delta Airlines increased after the merger with Northwest Airlines in the middle of 2008. The estimated coefficient of the trend variable is 0.008 but insignificant.

In column (4), the price elasticity of demand for Southwest Airlines is -0.45 and statistically significant at the 1% significant level. When air fare per passenger mile decreases by 1%, passenger miles increase by 0.45%. Its cross price elasticity of demand for American Airlines, United Airlines, and US Airways are 0.414, 0.215, and 0.273 and statistically significant at the 10%, 5% and 5% significant levels, respectively, indicating that they compete with each other. SW's cross price elasticity with Delta Airlines is -0.146 but is not significant. Income elasticity of demand is 1.505 and statistically significant at the 1% significant level, indicating an increase in passenger miles by 1.505% for every 1% increase in per capita income. The estimated coefficient of seasonal dummy variables for spring, summer, and fall are -0.09, 0.089, and 0.098 and statistically significant at the 1% significant level, indicating seasonality in passenger demand for airline service. The estimated coefficient of dummy variable for the September 11 attack is -0.002 but statistically insignificant. This means that SW's passenger miles were not affected by the September 11 attack. The estimated coefficient of trend is 0.041 and statistically significant at the 1% significant level.

In column (5), United Airlines's own price elasticity of demand is -0.298 and not significant. UA's cross price elasticity of demand with Southwest Airlines and US Airways are 1.089 and 0.640 and are statistically significant at the 1% and 5% levels, respectively. This means that they compete with each other in most routes. On the other hand, the cross price elasticity with DEL is -0.415 but not significant, indicating limited competition between them. Income elasticity of demand for UA is 2.131 and statistically significant at the 5% significant level. This means passenger miles increased by 2.131% for every 1% increase in per capita income. The estimated coefficients of summer and fall seasonal dummy variables are statistically significant at the 1% level, implying that passenger demand for UA's air service is seasonal. The estimated coefficient of dummy variable for the

September 11 attack is 0.054 but statistically insignificant, which means UA's passenger miles were not affected by the September 11 attack. The estimated coefficient for the merger of United Airlines is 0.262 and statistically significant at the 1% significant level. This indicates that passenger miles of United Airlines increased by 0.262% as a result of the merger with Continental Airlines in 2010. The estimated coefficient of trend is -0.04 and statistically significant at the 1% significant level.

In column (6), the price elasticity of demand for US Airways is -1.893 and statistically significant at the 1% significant level; therefore, US Airways passenger miles increase by 1.893% for every 1% decrease in its air fare per passenger mile. Its cross price elasticity of demand with American Airlines is 1.406 and statistically significant at the 1% significant level, meaning that they compete with each other. The cross price elasticity with Delta Airlines, Southwest Airlines, and United Airlines are not significant. This implies that these airlines have limited competition with one another. Income elasticity of demand is 0.495 and is not statistically significant. The estimated coefficient of seasonal dummy variable is 0.088 and statistically significant at the 1% significant level for summer; and are -0.036 and -0.027 and not significant for spring and fall, respectively, indicating weak seasonality. The estimated coefficient of dummy variable for the September 11 attack is -0.086 but not significant. The estimated coefficient for the merger between US Airways and America West is 0.241 and statistically significant at the 1% significant level. This indicates that the merger increased passenger miles of US Airways. The estimated coefficient of trend is -0.030 and statistically significant at the 5% significant level.

CONCLUSIONS

This study discussed the impact of economic and non-economic factors on demand of air passengers in the United States. The economic and statistical relationship of the factors on air passenger miles provides valuable information to understand the nature of the demand for U.S. air travel. In examining demand determinants, this study concludes that air fare, income, seasonality, and mergers among air carriers play significant roles in determining the demand for air passenger service. The study reveals that the major airlines in the United States compete with each other. However, the degree of competition differs on routes served by the airlines. This study found that demand of U.S. domestic air passengers is seasonal. Unexpected events such as the September 11 attack had a limited impact on passenger demand. Mergers among airline companies affected passengers' demand for U.S. domestic air travel significantly.

Acknowledgements

We would like to express our very great appreciation to the general editor of the Journal of the Transportation Research Forum, Dr. Michael W. Babcock, for his valuable and constructive suggestions to revise this research paper. We would also like to thank anonymous referees of the Journal of the Transportation Research Forum for their insightful and helpful comments on an earlier draft of this paper.

Endnotes

1. American Airlines (AA), Delta Airlines (DEL), Southwest Airlines (SW), United Airlines (UA), and US Airways (US).

2. Non fare component means the fare charged is not based on between two consecutive fare construction points. The point of origin and the point of destination of a fare component are fare construction points.

3. The percentage of the seats that were filled.

4. A no frills airline is an airline that offers low fares but eliminate all non-essential services, such as complimentary drinks and snacks, no free check-in baggage, in-flight entertainment systems, business-class seating, and so on.

5. The airline that sells seats to its customers, sets its fares independently, and does not use its own aircraft to operate the flight; it uses its partners' aircraft (the operating carriers) under the code-sharing agreement.

6. The airline with the aircraft whose passengers board under the code-sharing agreement.

7. Air fares vary over distances between origins and destinations. However, we use average air fare by airlines in the U.S. since the purpose of this study is to evaluate aggregate demand for air travel in the U.S. without considering segments between origins and destinations.

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Forecast of CO_2 Emissions From the U.S. Transportation Sector: Estimation From a Double Exponential Smoothing Model

by Jaesung Choi, David C. Roberts, and Eunsu Lee

This study examines whether the decreasing trend in U.S. CO_2 emissions from the transportation sector since the end of the 2000s will be shown across all states in the nation for 2012–2021. A double exponential smoothing model is used to forecast CO_2 emissions for the transportation sector in the 50 states and the U.S., and its findings are supported by the validity test of pseudo out-of-sample forecasts. We conclude that the decreasing trend in transportation CO_2 emissions in the U.S. will continue in most states in the future.

INTRODUCTION

The movement of people and goods is brought about through methods of transportation that use fossil fuel combustion, which proportionally emits carbon dioxide (CO_2) into the Earth's atmosphere. The impacts of this greenhouse gas (GHG) are fundamentally connected to transport modes, their energy supply structures, and the basic facilities over which they operate (Rodrigue 2013). As Lakshmanan and Han (1997) and Schipper et al. (2011) pointed out, CO_2 emissions from U.S. transportation energy use increased up until 2008 due to the growth of three factors: travel demand, population, and gross domestic product (GDP); however, both the consumption of fossil fuels by and CO_2 emissions from the transportation sector in the U.S. have shown significantly decreasing trends since 2008 because of multiple short-term and long-term factors, including slow growth after the economic recession, a hike in fuel prices, increasing fuel efficiency, and a decrease in vehicle mileage of passenger cars (U.S. Energy Information Administration 2014).

The decrease in U.S. CO_2 emissions in transportation over time is considerably related to the significant decrease in fuel consumption by light-duty vehicles,[1] which outweighs increases in fuel consumption by other modes. Fuel consumption by light-duty vehicles is projected to decrease from 4,539 million barrels of oil in 2012 to 4,335 million by 2040, which is the opposite of the increasing fuel consumption trend over the past three decades (The U.S. Energy Information Administration 2014). However, heavy-duty vehicles, airplanes, marine vessels, lubricants, and military use are expected to continue to increase fuel consumption for the next two decades (U.S. Energy Information Administration 2014).

Since the Kyoto Protocol in 1997, the international treaty has established binding obligations for both developed and developing countries to reduce emissions of greenhouse gases in the atmosphere. It is noteworthy that the U.S. was emitting the second highest CO_2 emissions in the world, but the long-term and significant decrease of CO_2 emissions from the transportation sector is now in progress (U.S. Department of Energy 2010).

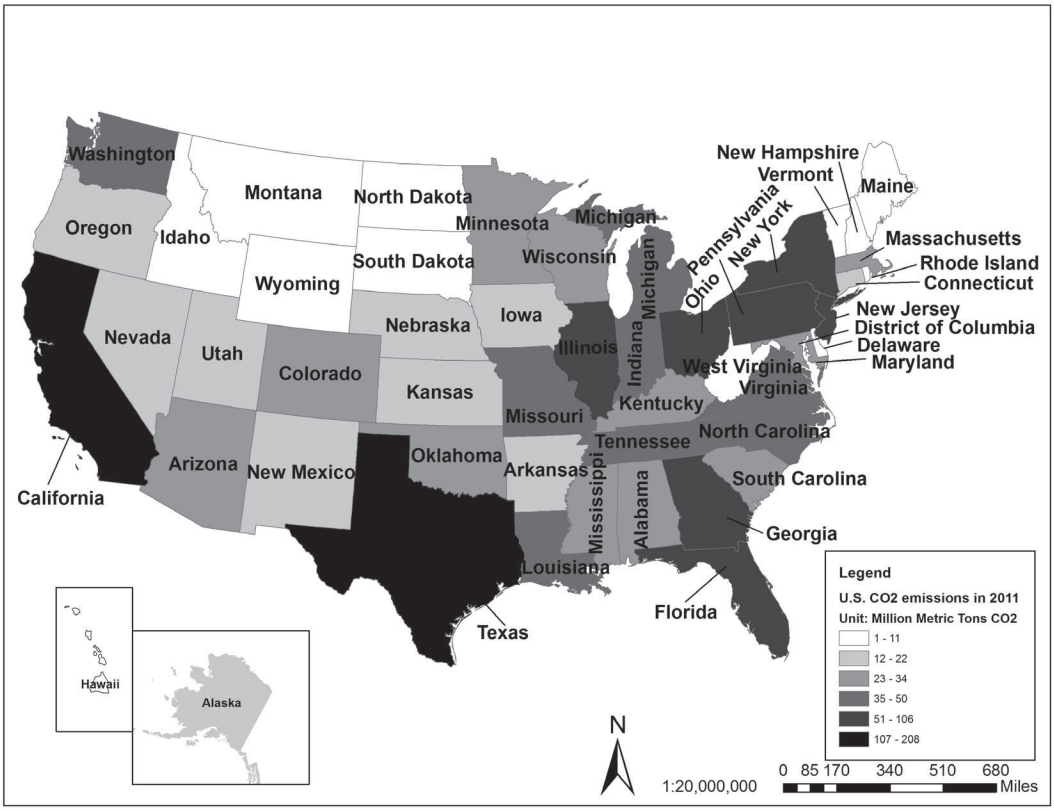
Historically, U.S. CO_2 emissions from the transportation sector have shown a trend over time, and thus they can be forecasted by using a statistical forecasting technique considering such a trend. Since Brown (1956) and Brown and Meyer (1960) developed the double exponential smoothing (DES) procedure to forecast a mean, a trend, and the variation of a noise, this method has been advanced by Goodman (1973), Gardner (1985), and Gijbels et al. (1999). For example, Goodman (1973) developed residual analysis to improve the forecast accuracy of DES models, while Gardner (1985) introduced general exponential smoothing to consider seasonality. In addition, Gijbels et al.

(1999) provided some insights into existing exponential smoothing theory by using a DES model within a nonparametric regression framework.

Numerous studies have used DES models to forecast in a variety of fields, including environmental pollution. Collins (1976) and Chu and Lin (1994) used a DES model to forecast levels of consolidated sales and earnings as well as the relationship between expected yearly recruitment levels and the necessary target requirements in high schools in Hong Kong, respectively. In 1999, Oh et al. (1999) applied a DES model to predict ozone formation in air pollution in South Korea; and Taylor (2003) forecasted electricity demand in England and Wales by using double seasonal exponential smoothing in order to minimize the seasonal effects of electricity consumption. Elliott and Timmermann (2008) empirically applied a DES model to predict U.S. inflation and stock returns, while Taylor (2012) used it to capture the density of the number of calls arriving at call centers. On the other hand, Xie and Su (2010) applied an exponential smoothing model to develop a river water pollution predictor in China, and Gupta (2011) developed an adaptive sampling strategy by using a DES model to evaluate carbon monoxide pollution by urban road traffic.

CO_2 emissions in transportation are different in each state in the U.S. as a result of their geographic characteristics, levels of economic development and population growth, and transportation and environmental regulations[2]. Figure 1 shows CO_2 emissions from the transportation sector by state in the U.S. for 2011. California and Texas emit the largest CO_2 emissions, while Florida, New York, Illinois, New Jersey, Ohio, Georgia, and Pennsylvania make the second largest CO_2 emissions, which are usually in areas of high development of urbanization and industrialization (U.S Energy Information Administration 2013).

Figure 1: U.S. CO_2 Emissions by State and the District of Columbia in 2011



Although the effect of fossil fuel energy consumption on future CO_2 emissions from private vehicle use in North America was analyzed in 2008 (Poudenx 2008) and the CO_2 emissions from the transportation sector in the U.S. were projected with other statistical models in 2012 (Bastani, Heywood and Hope 2012, Rentziou, Gkritza and Souleyrette 2012), their research was limited to a particular transportation industry and did not suggest future-specific CO_2 emissions per state in the U.S. over time. Most importantly, their findings lacked the provision of a validity test of their forecasts. For these reasons, this study forecasts U.S. CO_2 emissions by state from the overall transportation sector with the reliable validity test of pseudo out-of-sample forecasts.

The objectives of this study are i) to forecast national and state-level CO_2 emissions from 2012 to 2021 and ii) to review whether the decreasing trend in U.S. transportation CO_2 emissions will be shown across all states during this period. From the findings, this study will be able to provide administrators and state policy planners with detailed CO_2 emissions changes in the future in order to help them plan transportation CO_2 emissions regulations. The second section of this study presents discussions of alternative forecasting techniques, and the third section the state and federal air pollution regulations, including GHG. The fourth and fifth sections are the methodology and the data. After the results are presented, the conclusions discuss future CO_2 emissions changes in the United States.

DISCUSSIONS OF ALTERNATIVE FORECASTING TECHNIQUES

There exist many mathematical forecasting models today. These models include the autoregressive integrated moving average (ARIMA) technique and the seasonal autoregressive integrated moving average (S-ARIMA) technique. These methods are statistically sophisticated and mathematically complex methods that have been popular for forecasting the changes of time series in a broad number of applications (Zhai 2005). As a couple of researchers pointed out, these techniques regard past data and error terms of time series as essential information to forecast future changes. With a large amount of time series data, this technique shows quite a good accuracy of forecasting (Shumway and Stoffer 2011, Stock and Watson 2011).

However, as Zhai (2005) mentioned in her research, there are a few disadvantages of ARIMA and S-ARIMA techniques compared with a DES model. First, they have many possible models due to the number of possible combinations coming from the changes of the numbers in (seasonal) autoregressive terms, (seasonal) moving average terms, and/or (seasonal) autoregressive terms. Identifying the correct model among the possible models is likely to be subjective and depends on the experience and professional knowledge of the researcher. Second, "the underlying theoretical model and structural relationships are not as distinct as a DES model." (Zhai 2005, p.10)

STATE AND FEDERAL AIR POLLUTION REGULATIONS INCLUDING GHG

Of the 50 U.S. states, 32 have completed a climate change action plan to reduce their GHG emissions in their states since about 2005, which incorporates many specific policy recommendations (U.S. Environmental Protection Agency 2014C). For instance, the policy recommendations of Arkansas in 2008 included making a renewable portfolio standard, enacting a carbon tax, increasing energy efficiency, etc., and other participating states show similar policy recommendations for addressing GHG emissions (U.S. Environmental Protection Agency, 2014C).

A federal regulation to reduce air pollution initially started in 1955 as the Air Pollution Control Act and was complemented over time with the Clean Air Act (1963), the Air Quality Act (1967), the Clean Air Act (1970), and the Clean Air Act Amendments (1990). Since the middle of the 2000s with the Energy Policy Act (2005), Energy Independence and Security Act (2007), and President Obama's announcements of national policies (2009–2011 and 2014), stricter national air quality standards have been established by the U.S. Environmental Protection Agency (EPA). For more

detailed information, Table 1 provides each air pollution act and its key points regarding reducing air pollution and/or GHG emissions (U.S. Environmental Protection Agency, 2014A, 2014B).

Table 1: Federal Acts and Announcements and Their Key Points

Federal Acts and Announcements	Key points
Air Pollution Control Act (1955)	First federal-level act to prevent air pollution and provided a research fund to define scope and sources in air pollution.
Clean Air Act (1963)	Establishment of a national program for preventing air pollution and started researching into techniques to reduce it.
Air Quality Act (1967)	Authorized enforcement to reduce air pollution problems caused by interstate transport of pollutants.
Clean Air Act (1970)	Established national air quality standards.
Clean Air Act Amendments (1990)	Established a program to reduce 189 air pollutants and complemented provisions regarding the attainment of national air quality standards.
Energy Policy Act (2005)	Authorized to develop renewable energy or use innovative energy-efficient technology for reducing air pollution, including GHG emissions.
Energy Independence and Security Act (2007)	Authorized to increase energy efficiency and the production of clean renewable fuel.
Obama announcements of national policies (2009–2011 and 2014)	Presidential announcements to enhance GHG and fuel efficiency standards.

Note: Information about federal acts and announcements and their key points is from USEPA (2014A, 2014B).

METHODOLOGY

Let us define:

α = Smoothing weight for the level of the time series.
β_t = Time-varying slope.
ε_t = Disturbances.
u_t = Time-varying mean.
S_t = Smoothed state of the time series estimates u_t in Eq. (1).
S'_t = Smoothed state of the time series estimates u_t in Eq. (2).
S''_t = Smoothed values of the S'_t estimates β_t.
Y_t = Observed value at time t.
$\hat{Y}_t(m)$ = Forecast value ahead to m periods at time t.

We start with a simple exponential smoothing (SES) model to derive the DES model. The model equation for the SES is:

(1) $Y_t = \mu_t + \varepsilon_t, \qquad t = 1, \ldots, T.$

The smoothing equation is:

(2) $S_t = \alpha Y_t + (1 - \alpha) S_{t-1}.$

The m-step prediction equation is:

(3) $\hat{Y}_t(m) = S_t,$

The m-step prediction value $\hat{Y}_t(m)$ is estimated through Eq. (1) and Eq. (2) (Elliott and Timmermann 2008, SAS 9.2 User's Book 2013). Eq. (1) is an estimation of the time-varying mean and disturbances, while the smoothed state S_t that is computed after Y_t is observed is updated through Eq. (2). The smoothed state is a result of the combination of its actual observation plus the first lagged smoothed state with the control of smoothed weight. Exponential smoothing does not regard the effect of each past lag equally, and rather gives more weight to recent observations; hence, the smoothing weight between 0 and 1 is adjusted for this purpose. The smoothing process is backdated from time to time 1 to determine the starting value of the smoothed state at time 0 (Chatfield and Yar 1988). The SES model cannot deal with trending data since all predictions at time t from one-step-ahead to m-step-ahead are always the same as the value of in S_t Eq. (3). Thus, a DES model is used to reflect the effect of a trend in the data.

The model equation for this is:

(4) $Y_t = \mu_t + \beta_t \mathrm{t} + \varepsilon_t, \qquad \mathrm{t} = 1, \ldots, \mathrm{T}.$

The smoothing equations are:

(5) $S'_t = \alpha Y_t + (1-\alpha) S'_{t-1},$

(6) $S''_t = \alpha S'_t + (1-\alpha) S''_{t-1}.$

The m-step prediction equation is:

(7) $\hat{Y}_t(m) = \left(2 + \frac{\alpha \mathrm{m}}{1-\alpha}\right) S'_t - \left(1 + \frac{\alpha \mathrm{m}}{1-\alpha}\right) S''_t.$

The m-step prediction value $\hat{Y}_t(m)$ is the forecast value from the DES model, which is estimated by using the same process as in the SES model, but uses another smoothed series in Eq. (5) and Eq. (6). (Elliott and Timmermann 2008, SAS 9.2 User's Book 2013). The DES model is constructed when the SES method is twice run through the two different smoothed series in Eq. (5) and Eq. (6). The DES method can extrapolate nonseasonal patterns and trends such that the time series is smooth and has a slowly time-varying mean.

DATA

The data on CO_2 emissions[3] measured in million metric tons (MMT) from the transportation sector in the 50 states and the District of Columbia through fossil fuel combustion were obtained from the EPA for 1990–2011 (U.S. Environmental Protection Agency 2013). However, according to the central limit theorem, only 22 observations in a state may not be large enough to make the assumption that our sample data are well approximated by a normal distribution. To confirm this statistically, the normality of every state's CO_2 emissions data was tested by using an Anderson–Darling test, and the null hypothesis of no normality was not rejected, even at the 10% significance level.

Nevertheless, motor gasoline consumption data,[4] which are strongly correlated with CO_2 emissions from the transportation sector, were available for 1960–2011 from the State Energy Data System in the U.S. Energy Information Administration (USEIA) (U.S Energy Information Administration 2013). Thus, following some calculation processes, 29 new observations in each state from 1960 to 1989 were added for the state-level CO_2 emissions. First, we calculated the ratio of CO_2 emissions and motor gasoline consumption from 1990 to 2011 in a state. Second, we

summed the 22 calculated ratios and divided it by 22 to find the average annual CO_2 emissions per unit of motor gasoline consumption (the value of 22 was from the difference between 1990 and 2011). Third, motor gasoline consumption from 1960 to 1989 in a state was multiplied by the calculation result from step 2. Finally, the CO_2 emissions for the transportation sector from 1960 to 1989 by state were calculated through the third process. To check that the new dataset from 1960 to 2011 was normally distributed, an Anderson–Darling test in each state was again performed, and the non-normality assumption was statistically rejected at the 5% significance level.

Table 2 shows the CO_2 emissions from the transportation sector in the 50 states, the District of Columbia, and the U.S. for 1960–2011. Total U.S. CO_2 emissions increased until 2007, but decreased thereafter. Most states showed a similar trend, but 14 states have recently increased their CO_2 emissions: Alabama, Alaska, Hawaii, Idaho, Iowa, Louisiana, Nebraska, New Jersey, North Dakota, Ohio, Oklahoma, Tennessee, Texas, and Utah.

EMPIRICAL RESULTS

Before discussing the empirical results, this study's discussion is built around an assumption based on a technical report from the U.S. Energy Information Administration (2014). We assumed that motor gasoline consumption in the transportation sector will decrease in the next 10 years even though the U.S. economic recovery occurs, since a decrease in vehicle mileage from passenger cars, which is a possible cause of the recent decrease in CO_2 emissions in the U.S. transportation sector, is expected to be maintained.

As discussed in the methodology section, an SES model was not appropriate with the trending data of CO_2 emissions in the U.S. transportation sector, since it only gives reliable forecasts when a time series fluctuates about a base level. For this reason, a DES model that yields good forecasts with trending data was performed to forecast CO_2 emissions in the U.S. transportation sector.

Pseudo out-of-sample forecasts[5] were estimated to test the out-of-sample performances of the DES models in each state and the U.S. The models were fitted with the CO_2 emissions data from 1960 to 2005, and then the forecasted CO_2 emissions from 2006 to 2011 were compared with the actual observations during the same period, which were 10% of the sample size to verify forecasting accuracy. Table 3 provides the actual observations and 95% forecast confidence intervals for 2006–2011. The overall forecasting accuracies by the DES models in the 47 states and the U.S. are high; the actual observations of CO_2 emissions in 20 states are within the 95% forecast confidence intervals, which means that in 95% of all samples, they would contain the actual CO_2 emissions; 27 states and the U.S. only have one or two actual observations of CO_2 emissions among six of the 95% forecast confidence interval(s). On the other hand, Alaska, Idaho, North Carolina, and North Dakota show poor forecasting accuracies since three or four actual observations of CO_2 emissions are not within the 95% forecast confidence intervals for 2006–2011.

Next, the DES models in every state, the District of Columbia, and the U.S. were regressed with the transportation CO_2 emissions data from 1960 to 2011 by using the statistical package program SAS 9.3. The regression results in Table 4 show the parameter estimates for smoothed level, smoothed trend, smoothing weight, root mean square error (RMSE), and goodness of fit (R^2). Columns 1, 2, and 3 start with the information on smoothed level, smoothed trend, and smoothing weight, with the three concepts explained as follows: if a smoothed level is 1869 and a smoothed trend is -19.8, then the forecast value in the first forecast year has a value of 1849 (=1869-19.8). In the second forecast year, the forecast value is 1829 (=1849-19.8), and so on. A smoothing weight between 0 and 1 is adjusted to give more weight to recent observations.

All the models in the 50 states, the District of Columbia, and the U.S. in Table 4 have statistically significant smoothing weights at 1%, and the overall model fits run from 0.8 to 0.98, meaning that the DES models used show high model fits for 1960–2021. On the other hand, the RMSE increases

when the CO_2 emissions in a state increase, and thus California, Florida, and Texas show high RMSEs relative to the other states.

To make the estimation efficient and proper, a Ljung–Box chi-square test for error autocorrelation and a Dickey–Fuller test for stationarity were performed. In the DES models of each state and the U.S., the Ljung–Box chi-square tests showed that the autocorrelations of lags 1 and 2 in the prediction error are zero at the 1% significance level, while the Dickey–Fuller tests showed that a stationary time series is likely at the 1% significance level. The lagged variables in the DES models were assumed to be exogenous since the error terms were not serially correlated (Gujarati and Porter 2009).

In Table 4, the District of Columbia, Idaho, Iowa, Kansas, Nebraska, North Dakota, Oklahoma, South Dakota, Tennessee, and Utah are projected to increase CO_2 emissions from the transportation sector for 2012–2021 since their smoothed trends are greater than 0; however, owing to the possible poor forecasting accuracy of North Dakota in the pseudo out-of-sample forecast procedure, the findings for this state need to be carefully interpreted. On the other hand, 41 states are projected to show a decrease in CO_2 emissions because of the negative smoothed trends in Table 4. The levels of decreasing emissions will be different in each state, with California showing the largest CO_2emissions decrease due to the largest negative smoothed trend value of -5.31.

Table 5 shows the forecast values of CO_2 emissions from the transportation sector in the 50 states, the District of Columbia, and the U.S. for 2012–2021. The summation of CO_2emissions in all states is well matched to the forecast of U.S. CO_2 emissions. In California, CO_2 emissions from the transportation sector will significantly decrease by as much as one quarter of its 2011 CO_2 emissions by 2021, while Texas and Florida, which emitted the second and third highest CO_2 emissions in 2011, will gradually decrease their CO_2 emissions, too. In contrast, the 10 states in Table 4 projected to increase CO_2 emissions will increase their CO_2 emissions for 2012–2021, but their proportion of total CO_2 emissions will only range from 9% to 11% during this period; hence, the overall decreasing CO_2 emissions trend in the U.S. will remain. The findings for these 10 states might be a result of factors such as sudden population increases, less strict air pollution regulations in the transportation sector, and/or local economic growth through oil booms, agriculture production increases, or industrial development.

Table 2: CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 1960 to 2011 (Unit: MMT)

State/Year	1960	1970	1980	1990	2000	2007	2009	2011
Alabama	13.6	20.7	24.9	28.1	33.6	36.2	32.7	33.6
Arizona	6.7	11.9	17.0	22.8	32.5	38.0	33.1	31.7
Arkansas	8.5	13.3	15.9	16.2	21.0	21.2	20.4	20.1
Alaska	3.6	5.3	7.7	12.1	15.7	18.0	13.7	14.3
California	82.9	131.6	156.2	202.8	215.8	238.1	217.5	207.7
Colorado	8.6	14.2	19.0	19.2	25.7	31.5	29.4	28.9
Connecticut	9.0	13.3	14.1	14.7	16.2	17.7	16.4	15.8
Delaware	2.1	3.2	3.4	4.5	5.1	5.2	4.8	4.2
District of Columbia	2.2	2.6	1.8	1.8	1.8	1.2	1.1	1.2
Florida	23.4	41.3	59.6	81.4	100.6	115.7	99.4	105.6
Georgia	17.6	30.6	37.2	48.7	61.5	67.1	65.4	65.0
Hawaii	3.5	5.9	7.6	11.1	9.0	14.1	9.5	10.2
Idaho	3.5	5.3	6.1	6.4	8.8	9.6	8.7	9.1
Illinois	39.3	55.6	57.8	54.4	67.1	73.8	68.4	66.9
Indiana	25.2	35.0	36.8	40.9	46.6	45.5	40.9	42.9
Iowa	12.9	16.5	17.8	16.3	18.8	22.3	21.1	21.8
Kansas	12.1	16.5	17.9	19.3	18.8	19.6	19.8	19.1
Kentucky	13.3	21.2	25.3	26.4	31.5	35.0	32.7	32.6
Louisiana	23.1	36.3	49.9	48.9	61.0	50.8	47.2	50.2
Maine	4.4	5.8	6.2	8.3	8.6	9.1	8.6	8.4
Maryland	10.7	18.1	21.5	23.6	28.6	31.7	31.8	29.3
Massachusetts	17.1	24.3	25.2	28.9	32.1	33.6	30.8	30.9
Michigan	30.2	45.3	46.2	47.9	57.3	55.4	50.0	48.7
Minnesota	15.8	22.6	25.0	23.8	35.0	36.5	32.3	32.3
Mississippi	10.6	16.6	18.5	20.2	25.2	26.7	25.1	24.6
Missouri	21.2	29.9	32.0	33.8	39.5	42.9	39.7	39.4
Montana	4.0	5.7	6.5	5.9	7.5	9.0	8.0	8.2
Nebraska	6.5	8.6	9.2	10.5	12.2	12.6	12.5	14.2
Nevada	2.2	4.5	7.0	9.4	14.5	18.3	14.8	13.4
New Hampshire	2.2	3.6	4.1	5.2	7.3	7.5	7.2	7.1
New Jersey	33.1	45.2	50.1	57.1	65.0	72.6	62.3	66.0
New Mexico	6.5	9.1	11.8	14.9	15.3	15.6	14.0	14.1
New York	47.1	65.0	64.2	64.1	67.2	74.6	72.4	67.0
North Carolina	17.4	27.7	32.7	38.4	50.0	54.9	49.0	47.8
North Dakota	3.4	4.5	5.4	4.6	5.6	7.1	6.0	8.1
Ohio	41.3	57.8	61.1	56.1	68.9	72.9	64.6	65.2
Oklahoma	14.7	22.1	27.1	23.9	30.3	32.5	31.1	32.0
Oregon	9.7	15.4	19.1	20.0	22.7	24.5	22.9	21.2
Pennsylvania	44.1	56.4	61.6	59.5	70.6	72.2	66.4	64.5

Table 2 (continued)

State/Year	1960	1970	1980	1990	2000	2007	2009	2011
Rhode Island	2.8	3.8	4.0	4.1	4.7	4.4	4.3	4.0
South Carolina	8.8	14.4	18.0	22.0	27.1	32.2	31.3	30.9
South Dakota	3.5	4.6	4.9	4.7	5.8	6.4	6.3	6.6
Tennessee	15.7	24.5	32.4	32.8	41.6	46.3	41.6	43.1
Texas	64.2	102.3	130.2	152.5	182.9	205.1	190.2	195.5
Utah	4.8	7.9	10.2	10.6	15.7	18.5	16.4	17.5
Vermont	1.5	2.4	2.6	3.0	3.7	3.9	3.6	3.4
Virginia	16.9	26.9	32.9	41.5	48.6	57.2	50.9	48.3
Washington	15.8	25.3	30.1	41.0	44.8	47.9	42.2	41.2
West Virginia	6.9	9.5	11.7	10.4	12.7	12.5	11.4	11.2
Wisconsin	15.3	21.9	24.4	24.3	29.8	31.1	29.5	29.2
Wyoming	4.0	5.3	8.0	5.8	7.6	8.9	8.3	7.8
U.S. Total	814	1217	1420	1585	1880	2045	1868	1862

Note: The CO_2 emissions for the transportation sector from 1960 to 1989 by state and the District of Columbia were calculated using motor gasoline consumption data from 1960 to 1989 in USEIA (2013); the CO_2 emissions from 1990 to 2011 were obtained from USEPA (2013).

Table 3: Pseudo Out-of-Sample Forecasts of CO_2 Emissions (MMT) from the Transportation Sector to Evaluate the DES Models' Performances by State, the District of Columbia, and the U.S. from 2006 to 2011

State/Year	2006	2007	2008	2009	2010	2011
Alabama	35.5 (33.7, 37.6)	36.1 (34.2, 38.1)	33.5† (34.7, 38.7)	32.6 (31.8, 35.7)	33.7 (30.1, 34.0)	33.5 (31.1, 35.1)
Arizona	38.2 (36.7, 39.0)	37.9† (38.0, 40.4)	35.0† (37.3, 39.7)	33.1 (33.2, 35.6)	32.0 (30.4, 32.8)	31.7 (29.3, 31.7)
Arkansas	20.6 (19.1, 22.4)	21.1 (19.1, 22.4)	20.5 (19.6, 22.8)	20.3 (19.0, 22.3)	20.4 (18.7, 21.9)	20.1 (18.7, 21.9)
Alaska	19.1 (17.9, 21.6)	18.0† (18.2, 22.0)	15.4† (17.3, 21.1)	13.6† (14.7, 18.5)	15.0 (12.1, 15.9)	14.2 (12.2, 16.0)
California	234 (221, 245)	238 (226, 250)	222† (230, 254)	217 (212, 237)	215 (202, 226)	207 (198, 223)
Colorado	30.7 (29.2, 32.3)	31.5 (30.1, 33.2)	30.1† (30.8, 34.0)	29.3 (29.3, 32.5)	29.8 (27.9, 31.1)	28.8 (28.1, 31.2)
Connecticut	17.6† (18.1, 20.0)	17.6 (17.0, 18.9)	16.7 (16.6, 18.6)	16.4 (15.7, 17.6)	16.1 (15.1, 17.0)	15.8 (14.7, 15.7)
Delaware	5.1 (4.7, 5.6)	5.2 (4.8, 5.6)	5.0 (4.9, 5.7)	4.8 (4.6, 5.4)	4.4 (4.4, 5.2)	4.2 (4.0, 4.8)
District of Columbia	1.23 (1.15, 1.56)	1.22 (0.94, 1.35)	1.07 (0.90, 1.32)	1.12 (0.77, 1.18)	1.10 (0.82, 1.24)	1.22 (0.83, 1.25)
Florida	116 (111, 124)	115 (113, 127)	105† (111, 125)	99 (99, 113)	105† (89, 103)	105 (95, 109)
Georgia	68.3 (68.2, 74.4)	67.0 (66.8, 73.0)	61.2† (64.4, 70.7)	65.4† (56.7, 62.9)	66.7 (61.2, 67.4)	65.0 (63.9, 70.1)
Hawaii	13.0 (12.5, 14.6)	14.0 (12.5, 14.6)	9.71† (13.6, 15.7)	9.44 (7.93, 10.0)	9.65† (7.14, 9.28)	10.23† (7.81, 9.95)
Idaho	9.30 (8.17, 9.31)	9.63 (8.92, 10.06)	8.78† (9.36, 10.51)	8.68 (8.22, 9.36)	9.47† (7.94, 9.08)	9.13 (8.97, 10.12)
Illinois	73.3† (75.3, 87.9)	73.7 (68.9, 81.5)	69.8 (67.9, 80.5)	68.3 (62.1, 74.7)	67.6 (60.2, 72.8)	66.8 (60.0, 72.6)
Indiana	46.4 (42.2, 49.0)	45.5 (43.0, 49.9)	42.3† (42.4, 24.2)	40.8 (39.0, 45.8)	42.9 (36.7, 43.5)	42.9 (38.2, 45.1)
Iowa	21.8 (20.5, 23.4)	22.3 (21.0, 23.9)	21.5 (21.4, 24.3)	21.1 (20.1, 23.0)	21.5 (19.4, 22.2)	21.7 (20.0, 22.9)
Kansas	19.0 (16.5, 19.8)	19.5 (17.1, 20.4)	19.0 (17.8, 21.1)	19.7 (17.6, 20.9)	19.6 (18.2, 21.4)	19.0 (18.1, 21.4)
Kentucky	33.4 (32.1, 36.3)	34.9 (31.8, 36.0)	32.1† (33.1, 37.2)	32.6 (30.7, 34.8)	33.2 (30.4, 34.5)	32.6 (30.9, 35.0)
Louisiana	55.0 (46.6, 54.8)	50.8 (49.5, 57.7)	47.9 (46.8, 55.0)	47.2 (43.4, 51.6)	50.1† (41.8, 50.0)	50.2 (44.3, 52.5)
Maine	9.41 (8,67, 10.3)	9.06 (8.80, 10.4)	8.20† (8.49, 10.1)	8.57 (7.59, 9.25)	8.51 (7.59, 9.52)	8.38 (7.56, 9.22)
Maryland	42.2 (39.0, 45.1)	42.8 (39.6, 45.6)	40.3 (40.3, 46.4)	39.6 (36.4, 42.5)	40.1 (35.6, 41.6)	39.3 (36.8, 42.8)
Massachusetts	33.0† (33.3, 36.3)	33.5 (31.6, 34.5)	33.4 (32.1, 35.1)	30.7† (32.0, 34.9)	30.8 (28.4, 31.3)	30.9 (28.4, 31.4)
Michigan	55.7 (52.1, 59.1)	55.3 (52.0, 59.0)	51.3† (51.6, 58.6)	49.9 (45.6, 52.6)	49.8 (44.5, 51.4)	48.6 (45.3, 52.3)
Minnesota	36.1 (34.9, 39.4)	36.5 (34.3, 38.8)	34.6 (34.4, 39.0)	32.2 (32.2, 36.7)	32.7 (29.1, 33.6)	32.3 (29.5, 34.0)

Table 3 (continued)

State/Year	2006	2007	2008	2009	2010	2011
Mississippi	26.8 (23.8, 26.9)	26.6 (25.4, 28.5)	25.6 (25.4, 28.5)	25.0 (24.1, 27.2)	25.2 (23.2, 26.2)	24.6 (23.4, 26.5)
Missouri	42.2 (39.0, 45.1)	42.8 (39.6, 45.6)	40.3 (40.3, 46.4)	39.6 (36.4, 42.5)	40.1 (35.6, 41.6)	39.3 (36.8, 42.8)
Montana	8.5 (7.5, 9.0)	9.0 (7.9, 9.4)	8.3† (8.4, 9.9)	7.9† (8.0, 9.5)	8.1 (7.5, 9.0)	8.2 (7.4, 8.9)
Nebraska	12.4 (11.3, 13.4)	12.6 (11.5, 13.6)	12.3 (11.7, 13.8)	12.5 (11.2, 13.3)	14.6 (11.4, 13.6)	14.1 (14.8, 17.0)
Nevada	18.0 (16.8, 18.0)	18.2 (18.1, 19.3)	16.3† (18.4, 19.6)	14.8† (15.9, 17.1)	13.9 (13.6, 14.8)	13.3 (12.4, 13.6)
New Hampshire	7.2 (6.8, 7.8)	7.4 (6.6, 7.6)	7.2 (6.9, 7.8)	7.2 (6.7, 7.7)	7.2 (6.6, 7.6)	7.0 (6.6, 7.6)
New Jersey	68.8 (65.7, 73.4)	72.6 (66.5, 74.2)	73.5 (69.9, 77.6)	62.2† (71.5, 79.2)	63.7 (61.1, 68.8)	65.9 (58.9, 66.6)
New Mexico	16.0 (14.0, 16.9)	15.5 (14.5, 17.4)	14.2† (14.3, 17.1)	14.0 (13.0, 15.8)	13.6 (12.3, 15.2)	14.1 (11.9, 14.7)
New York	74.8 (69.4, 82.4)	74.6 (69.6, 82.7)	74.3 (69.2, 82.2)	72.3 (68.6, 81.6)	72.3 (66.5, 79.5)	66.9 (65.7, 78.7)
North Carolina	53.1 (53.0, 56.9)	54.9 (51.2, 55.1)	53.4† (54.1, 58.1)	48.9† (50.8, 54.8)	49.2† (43.7, 47.6)	47.7 (46.2, 50.1)
North Dakota	6.2 (5.8, 7.0)	7.1† (5.7, 6.9)	6.3† (6.4, 7.6)	6.0† (6.1, 7.2)	6.9† (5.6, 6.8)	8.0† (6.2, 7.3)
Ohio	72.1 (67.6, 75.7)	72.9 (68.6, 76.6)	69.0† (69.5, 77.6)	64.5 (63.2, 71.2)	65.9† (57.0, 65.0)	65.2 (60.9, 69.0)
Oklahoma	31.7 (28.0, 33.0)	32.5 (29.2, 34.2)	32.3 (30.3, 35.3)	31.0 (30.3, 35.3)	32.2 (28.9, 33.9)	31.9 (29.6, 34.6)
Oregon	23.9 (22.4, 25.2)	24.5 (23.0, 25.8)	22.7† (23.7, 26.4)	22.9 (21.1, 23.8)	22.1 (21.1, 23.9)	21.2 (20.3, 23.0)
Pennsylvania	72.4 (70.1, 78.2)	72.2 (68.3, 76.4)	67.4† (67.9, 76.0)	66.4 (59.5, 67.6)	66.0† (60.7, 68.8)	64.4 (61.4, 69.5)
Rhode Island	4.4 (4.0, 4.5)	4.3 (4.1, 4.6)	4.1 (4.1, 4.6)	4.2 (3.8, 4.3)	4.2 (3.9, 4.4)	4.0 (3.9, 4.4)
South Carolina	32.0 (30.2, 33.7)	32.2 (31.1, 34.6)	30.6† (31.3,34.8)	31.2 (29.7, 33.2)	31.2 (29.7, 33.2)	30.8 (29.6, 33.1)
South Dakota	6.1 (5.6, 6.6)	6.4 (5.6, 6.7)	6.0 (5.9, 7.0)	6.2 (5.5, 6.6)	6.5 (5.7, 6.8)	6.5 (6.1, 7.1)
Tennessee	45.8 (43.8, 48.4)	46.2 (44.0, 48.6)	42.9† (44.3, 48.9)	41.5 (39.9, 44.5)	43.1† (37.9, 42.5)	43.1 (40.1, 44.8)
Texas	202 (186, 206)	205 (194, 214)	197 (198, 218)	190† (190, 210)	194 (179, 199)	195 (182, 201)
Utah	18.5† (16.2, 17.9)	18.5 (18.3, 20.0)	17.0† (18.3, 20.0)	16.4 (16.2, 17.9)	16.3 (15.1, 16.8)	17.4 (15.1, 16.8)
Vermont	3.8 (3.7, 4.1)	3.8 (3.7, 4.1)	3.5 (3.6, 4.0)	3.6 (3.2, 3.6)	3.5 (3.3, 3.7)	3.4 (3.2, 3.6)
Virginia	56.9 (55.4, 60.1)	57.2 (56.3, 61.0)	52.7 (56.0, 60.7)	50.8 (49.7, 54.3)	50.4 (46.7, 51.4)	48.3 (46.6, 51.2)
Washington	44.8 (40.3, 46.7)	47.8 (41.8, 48.1)	42.9 (45.1, 51.5)	42.1 (41.0, 47.3)	41.2 (38.9, 45.2)	41.1 (37.5, 43.8)

Table 3 (continued)

State/Year	2006	2007	2008	2009	2010	2011
West Virginia	12.5 (11.6, 13.6)	12.4 (11.6, 13.6)	11.0† (11.5, 13.5)	11.3 (9.8, 11.9)	11.6 (9.9, 12.0)	11.2 (10.4, 12.5)
Wisconsin	30.8 (28.9, 31.9)	31.1 (29.5, 32.6)	30.1 (29.8, 32.9)	29.5 (28.3, 31.3)	30.3 (27.4, 30.4)	29.1 (28.8, 31.9)
Wyoming	8.6 (7.5, 9.3)	8.8 (7.8, 9.6)	8.6 (8.1, 9.9)	8.3 (7.9, 9.7)	8.4 (7.5, 9.3)	7.7 (7.5, 0.3)
U.S. Total	2028 (1962, 2106)	2045 (1990, 2133)	1929† (1998, 2141)	1867 (1807, 1950)	1891† (1731, 1874)	1862 (1801, 1944)

Note: † indicates that actual CO_2 emissions are not within the 95% forecast confidence interval. Actual CO_2 emissions are out of the parentheses, and 95% forecast confidence intervals are in the parentheses.

CONCLUSIONS

The increase in CO_2 emissions in the world has adversely affected sustainable development for human life and the Earth's ecosystems, resulting in global warming and climate change; therefore, the recent decrease in CO_2 emissions from the U.S. transportation sector and its long-term decreasing trend found in this study are meaningful for the world's efforts to reduce CO_2 emissions. This study found that the decreases in CO_2 emissions in most states are not temporary, but rather will continuously occur for the next decade. By 2021, the U.S. is projected to emit CO_2 of 1664 MMT from the transportation sector, a reduction of 198 MMT compared with 2011. This reduced amount in 2021 will account for almost all the CO_2 emissions from California in 2011, which emitted the most CO_2 emissions in the nation.

A major finding from the empirical results is that while CO_2 emissions by most of the U.S. states for the next 10 years will show a downward pattern, 10 states are projected to show an increasing tendency of transportation CO_2 emissions. One possible hypothesis to explain this difference across states is probably related to whether a state has a GHG emissions reduction plan in place or not. Looking at these 10 states, eight of them have not actually completed any climate change action plan within their boundaries, compared with most of the other states trying to address GHG emissions. This could imply much more importance needs to be placed on environmental policies for CO_2 emissions reduction in the transportation sector, not only at national but at state level, too. One caveat, nevertheless, is that from this finding, the policymakers should really aim at those areas where the policy might be warranted, i.e., by the Lucas Critique,[6] if a policy changes, the outcomes of sample forecasts will be wrong.

This study has a limitation based on the data used. The CO_2 emissions data from 1960 to 1989 for each state and the U.S. were estimated from motor gasoline consumption data to find the best possible approximation; if original data during the period were available from the EPA, we could have estimated more accurate results for our CO_2 emissions forecasts from the U.S. transportation sector.

Table 4: Parameter Estimates, a Measure of Accuracy, and Goodness of Fit for Projections of CO_2 Emissions by State, the District of Columbia, and the U.S. for 2012–2021

State	Smoothed Level	Smoothed Trend	Smoothing Weight	RMSE	R^2
Alabama	33.59	-0.12	0.56 ***	1.06	0.97
Arizona	31.80	-0.63	0.83 ***	0.77	0.99
Arkansas	20.28	-0.13	0.51 ***	0.78	0.95
Alaska	14.64	-0.50	0.53 ***	1.13	0.93
California	211.74	-5.31	0.59 ***	6.43	0.97
Colorado	29.27	-0.37	0.57 ***	0.84	0.98
Connecticut	16.05	-0.35	0.58 ***	0.51	0.94
Delaware	4.46	-0.21	0.51 ***	0.20	0.94
District of Columbia	1.17	0.02	0.57 ***	0.10	0.94
Florida	105.33	-0.33	0.56 ***	3.47	0.98
Georgia	65.41	-0.04	0.52 ***	1.99	0.98
Hawaii	10.10	-0.19	0.55 ***	0.90	0.87
Idaho	9.15	0.04	0.51 ***	0.34	0.96
Illinois	67.44	-1.06	0.62 ***	3.25	0.85
Indiana	42.84	-0.22	0.48 ***	1.72	0.91
Iowa	21.69	0.16	0.71 ***	0.71	0.91
Kansas	19.31	0.004	0.44 ***	0.80	0.84
Kentucky	32.88	-0.12	0.47 ***	1.04	0.96
Louisiana	49.85	-0.20	0.43 ***	2.20	0.95
Maine	8.50	-0.08	0.43 ***	0.41	0.91
Maryland	29.78	-0.87	0.70 ***	1.50	0.98
Massachusetts	31.04	-0.38	0.61 ***	0.85	0.96
Michigan	49.05	-1.00	0.73 ***	1.76	0.94
Minnesota	32.63	-0.59	0.58 ***	1.13	0.96
Mississippi	24.97	-0.32	0.55 ***	0.78	0.97
Missouri	39.60	-0.44	0.70 ***	1.50	0.94
Montana	8.23	-0.004	0.41***	0.39	0.89
Nebraska	14.05	0.44	0.63 ***	0.62	0.91
Nevada	13.48	-0.69	0.87 ***	0.49	0.98
New Hampshire	7.15	-0.07	0.59 ***	0.23	0.98
New Jersey	65.91	-0.57	0.42 ***	2.63	0.93
New Mexico	14.13	-0.21	0.45 ***	0.71	0.93
New York	70.25	-1.59	0.48 ***	3.21	0.80
North Carolina	48.29	-1.25	0.71 ***	1.26	0.98
North Dakota	7.10	0.26	0.36 ***	0.38	0.84
Ohio	65.38	-0.55	0.77 ***	2.03	0.94
Oklahoma	31.91	0.08	0.47 ***	1.23	0.93
Oregon	21.61	-0.72	0.66 ***	0.72	0.96
Pennsylvania	64.78	-1.30	0.83 ***	2.08	0.93

Table 4 (continued)

State	Smoothed Level	Smoothed Trend	Smoothing Weight	RMSE	R^2
Rhode Island	4.11	-0.08	0.56 ***	0.12	0.93
South Carolina	31.04	-0.07	0.49 ***	0.90	0.98
South Dakota	6.49	0.09	0.54 ***	0.26	0.89
Tennessee	43.03	0.005	0.64 ***	1.28	0.97
Texas	195.03	-0.34	0.53 ***	5.22	0.98
Utah	17.13	0.22	0.62 ***	0.59	0.97
Vermont	3.47	-0.08	0.61 ***	0.11	0.97
Virginia	48.99	-1.64	0.73 ***	1.38	0.98
Washington	41.78	-0.67	0.48 ***	1.76	0.96
West Virginia	11.43	-0.14	0.50 ***	0.54	0.89
Wisconsin	29.47	-0.43	0.68 ***	0.78	0.97
Wyoming	8.14	-0.17	0.49 ***	0.44	0.90
U.S. Total	1869	-19.81	0.75 ***	41.10	0.98

Note: *** indicate significance at the 1% level. The smoothed level and trend are not related to the hypothesis tests. The smoothed level and trend and smoothing weight use a unit of MMT CO_2.

Table 5: Forecasted Values of CO_2 Emissions from the Transportation Sector by State, the District of Columbia, and the U.S. from 2012 to 2021 (Unit: MMT)

State/Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Alabama	33.4	33.2	33.1	33.0	32.9	32.8	32.6	32.5	32.4	32.3
Arizona	31.0	30.4	29.8	29.1	28.5	27.9	27.2	26.6	26.0	25.3
Arkansas	20.0	19.9	19.8	19.6	19.5	19.4	19.2	19.1	18.9	18.8
Alaska	13.7	13.2	12.7	12.2	11.7	11.2	10.7	10.2	9.7	9.2
California	202.8	197.5	192.2	186.9	181.5	176.2	170.9	165.6	160.3	155.0
Colorado	28.6	28.2	27.9	27.5	27.1	26.7	26.4	26.0	25.6	25.2
Connecticut	15.4	15.1	14.7	14.4	14.0	13.7	13.3	12.9	12.6	12.2
Delaware	4.0	3.8	3.6	3.4	3.2	3.0	2.8	2.6	2.3	2.1
District of Columbia	1.2	1.2	1.3	1.3	1.3	1.3	1.3	1.4	1.4	1.4
Florida	104.7	104.4	104.0	103.7	103.4	103.0	102.7	102.4	102.1	101.7
Georgia	65.3	65.2	65.2	65.2	65.1	65.1	65.0	65.0	64.9	64.9
Hawaii	9.7	9.5	9.3	9.1	8.9	8.8	8.6	8.4	8.2	8.0
Idaho	9.2	9.2	9.3	9.3	9.4	9.4	9.5	9.5	9.5	9.6
Illinois	65.7	64.6	63.6	62.5	61.4	60.4	59.3	58.3	57.2	56.1
Indiana	42.3	42.1	41.9	41.7	41.5	41.2	41.0	40.8	40.6	40.3
Iowa	21.9	22.0	22.2	22.4	22.5	22.7	22.9	23.0	23.2	23.4
Kansas	19.3	19.3	19.3	19.3	19.3	19.3	19.3	19.3	19.3	19.3
Kentucky	32.6	32.4	32.3	32.2	32.0	31.9	31.8	31.7	31.5	31.4
Louisiana	49.3	49.1	48.9	48.7	48.5	48.3	48.1	47.9	47.7	47.5
Maine	8.3	8.2	8.1	8.0	7.9	7.8	7.7	7.6	7.5	7.4
Maryland	28.4	27.5	26.6	25.7	24.9	24.0	23.1	22.2	21.4	20.5
Massachusetts	30.4	30.0	29.6	29.2	28.8	28.4	28.1	27.7	27.3	26.9
Michigan	47.6	46.6	45.6	44.6	43.6	42.6	41.6	40.6	39.6	38.6
Minnesota	31.6	31.0	30.4	29.8	29.2	28.6	28.0	27.4	26.8	26.2
Mississippi	24.3	24.0	23.7	23.4	23.1	22.7	22.4	22.1	21.8	21.4
Missouri	38.9	38.5	38.0	37.6	37.1	36.7	36.3	35.8	35.4	34.9
Montana	8.2	8.2	8.2	8.2	8.2	8.1	8.1	8.1	8.1	8.1
Nebraska	14.7	15.1	15.6	16.0	16.5	16.9	17.3	17.8	18.2	18.7
Nevada	12.6	11.9	11.3	10.6	9.9	9.2	8.5	7.8	7.1	6.4
New Hampshire	7.0	6.9	6.8	6.8	6.7	6.6	6.5	6.5	6.4	6.3
New Jersey	64.5	63.9	63.3	62.8	62.2	61.6	61.0	60.5	59.9	59.3
New Mexico	13.6	13.4	13.2	13.0	12.8	12.6	12.4	12.1	11.9	11.7
New York	66.7	65.1	63.5	61.9	60.3	58.7	57.1	55.5	53.9	52.3
North Carolina	46.5	45.2	44.0	42.7	41.4	40.2	38.9	37.7	36.4	35.2
North Dakota	7.8	8.0	8.3	8.6	8.8	9.1	9.4	9.6	9.9	10.1
Ohio	64.6	64.1	63.5	63.0	62.4	61.8	61.3	60.7	60.2	59.6
Oklahoma	32.0	32.1	32.2	32.3	32.4	32.5	32.6	32.7	32.8	32.9
Oregon	20.5	19.8	19.0	18.3	17.6	16.9	16.2	15.4	14.7	14.0
Pennsylvania	63.2	61.9	60.6	59.3	58.0	56.7	55.4	54.1	52.8	51.5
Rhode Island	3.9	3.8	3.7	3.6	3.6	3.5	3.4	3.3	3.2	3.1

Table 5 (continued)

State/Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
South Carolina	30.8	30.8	30.7	30.6	30.5	30.5	30.4	30.3	30.2	30.2
South Dakota	6.6	6.7	6.8	6.9	7.0	7.1	7.2	7.3	7.4	7.5
Tennessee	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0	43.0
Texas	194.3	194.0	193.6	193.3	193.0	192.6	192.3	191.9	191.6	191.2
Utah	17.4	17.7	17.9	18.1	18.4	18.6	18.8	19.0	19.3	19.5
Vermont	3.3	3.2	3.1	3.0	2.9	2.8	2.8	2.7	2.6	2.5
Virginia	46.7	45.0	43.4	41.7	40.1	38.5	36.8	35.2	33.5	31.9
Washington	40.3	39.7	39.0	38.3	37.6	37.0	36.3	35.6	35.0	34.3
West Virginia	11.1	10.9	10.8	10.6	10.5	10.3	10.2	10.0	9.9	9.7
Wisconsin	28.8	28.4	27.9	27.5	27.0	26.6	26.2	25.7	25.3	24.9
Wyoming	7.7	7.6	7.4	7.2	7.0	6.9	6.7	6.5	6.3	6.1
U.S. Total	1843	1823	1803	1783	1763	1744	1724	1704	1684	1664

Endnotes

1. The EPA defines light-duty vehicles (i.e., passenger cars) as carrying a maximum Gross Vehicle Weight Rating of less than 8500 lbs (The U.S. Energy Information Administration 2014).

2. These variables are embodied in the trend of the change in CO_2 emissions. The change of CO_2 emissions in the transportation sector are highly related to these factors, so if we use those variables as explanatory variables with CO_2 emissions variable in a forecasting model, then it could result in multicollinearity. Also, DES models only use one variable that we are trying to forecast. For example, suppose we are interested in forecasting CO_2 emissions in the transportation sector. The dependent variable and independent variables using the DES model will be calculated through the mathematical formula of the DES model from only the one variable.

3. CO_2 emissions per kWh in electricity from coal-fired thermal power stations are reported higher than in CO_2 emissions per kWh from various other fuels (Hutton 2013).

4. CO_2 emissions are generated by both gasoline consumption and diesel consumption data. Due to the non-availability of diesel consumption data to the public, this study could only use gasoline consumption data.

5. Pseudo out-of-sample forecasting is generally used to test the real-time accuracy of a forecasting model. The mechanism is as follows: Select a date close to the end of the sample, estimate a forecasting model with data up to that date, utilize the estimated forecasting model to make a forecast after the date, and then compare the forecasted values corresponding to the original data (Stock and Watson 2011).

6. The Lucas Critique derived from his work on macroeconomic policymaking implies that evaluation of the effects of economic policy based on the historical data might not be appropriate (Lucas 1976).

Acknowledgements

This research was part of Jaesung Choi's dissertation and was funded by the Mountain-Plains Consortium, the Region 8 University Transportation Center at North Dakota State University.

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State Variation in Railroad Wheat Rates

by Michael W. Babcock, Matthew McKamey, and Phillip Gayle

Wheat shippers in the Central Plains states have no cost effective transportation alternative to railroads. Wheat produced in these areas moves long distances to domestic processing and consumption locations or to ports for export. Wheat shippers in the Great Plains don't have direct access to barge loading locations and trucks provide no intermodal competition for these movements. Wheat shippers in Montana and North Dakota are highly dependent on rail transport because they are distant from barge loading locations and intra-railroad competition is limited. In North Dakota, the BNSF controls 78% of the Class I rail mileage, and in Montana, the BNSF controls 94%. Montana ships nearly 100% of its wheat by rail.

Unlike Montana and North Dakota, the BNSF and UP have roughly equal track mileage in Kansas. The BNSF has 44% of the Class I rail mileage and the UP, 55%. Also, both railroads serve the major Kansas grain storage and market centers.

A 2010 USDA study found that in 1988, Montana and North Dakota had the highest rail grain revenue per ton-mile of the 10 major grain producing states. By 2007 this was no longer the case. The overall objective of the paper is to investigate railroad pricing behavior for the shipment of North Dakota, Kansas, and Montana wheat. Specific objectives include (1) develop a model to measure the impacts of railroad costs and competition on rail wheat rates for North Dakota, Kansas, and Montana, (2) identify and measure the major cost determinants of rail wheat prices, and (3) measure intermodal competition by comparing rail wheat rates in captive markets (Montana and North Dakota) to one with more intermodal competition (Kansas).

The results indicate that there is little difference in average Montana and Kansas rail wheat rates per ton-mile. However, North Dakota average railroad wheat prices per-ton mile are higher than average Kansas rates per ton-mile.

INTRODUCTION

Railroads were the most heavily regulated transportation mode prior to passage of the Staggers Rail Act in 1980. Deregulation gave the railroads a great deal of pricing flexibility that was previously unavailable. Prices between variable cost and 180% of variable cost were not subject to regulatory jurisdiction and review. The Staggers Act set time limits for ICC decisions regarding abandonments and mergers. Thus Class I railroads were able to quickly abandon or sell branch lines that lost money. Mergers reduced the number of Class I railroads from 40 in 1980 to seven today.

Deregulation has benefited both the railroads and the shippers. For the rail industry, the average rate of return on investment increased from less than 3% in the 1970s to 4.4% for the 1980s, 7.64% in the 1990s, and 8.21% in the 2000s (AAR, various years). The average railroad rate of return on the shareholders' equity rose from 2.44% in the 1970s to 7.37% in the 1980s, 9.51% in the 1990s, and 9.38% in the 2000s (AAR, various years).

According to Winston and Grimm (2000), the net annual benefits to shippers were more than $12 billion in 1999 dollars in the first decade following passage of the Staggers Act. Shippers have benefited from 20 years of declining rail rates (inflation adjusted revenue per ton-mile) as well as the preservation of rural area lines sold or leased to short line railroads (Prater 2010).

Railroads are important for transporting agricultural commodities from producing regions to domestic processing locations and export ports. These shipments involve large scale movement of low value, bulk commodities over long distances, and thus rail service is virtually the only cost effective shipping alternative available.

According to Prater (2010), nine of the top 10 wheat producing states are more than 150 miles from barge transportation on the Mississippi River, which provides the most significant intermodal competition to railroads for long distance movements of grain to export ports. Wheat shippers in the Great Plains states have no cost effective transportation alternative to railroads. Wheat produced in these areas moves long distances to domestic processing and consumption locations or to ports for export. Wheat shippers in the Great Plains don't have direct access to barge loading locations and trucks provide no intermodal competition for these movements.

Wheat shippers in Montana and North Dakota are highly dependent on rail transport because they are distant from barge loading locations and trucks are not cost effective for long distance shipments of wheat. Cutler et al. (2009), found that Montana ships nearly 100% of its wheat by rail.

Intrarailroad competition is limited in both North Dakota and Montana. In North Dakota, the Burlington Northern Santa Fe (BNSF) controls 78% of the Class I rail mileage (Table 1). The only other Class I railroad in North Dakota is the SOO Line Railroad Company, controlled by the Canadian Pacific Railroad. The regional and local railroads are bridge carriers for the Class I railroads and thus provide little direct intrarailroad competition. However, depending on the railroad network, non-Class I railroads may contribute to intrarailroad competition. For example, in North Dakota, the Dakota, Missouri Valley and Western (DMVW) is an affiliate of the Canadian Pacific (CP) but it serves areas of the state that the BNSF does also, but not in the CP. Thus DMVW competes with BNSF for these shipments. Also in North Dakota, the Red River Valley and Western (RRVW) is an affiliate of BNSF but serves many areas of the state where there is a strong CP presence. Thus RRVW competes with CP for these shipments. So in essence the regional and local railroads may compete on behalf of the Class I railroads.

In Montana, the BNSF controls 94% of the Class I railroad mileage (Table 2). The only other Class I railroad is the Union Pacific (UP) with only 125 miles of track. Regional operators include Montana Rail Link (MRL) with 937 miles of track and Dakota, Missouri Valley and Western Railroad (DMVWR). The regional classification of DMVWR is somewhat misleading as the railroad only operates 51 miles of track in Montana. While MRL operates a large amount of track, it serves as a bridge carrier of BNSF and thus doesn't provide intramodal competition. The MRL operates and maintains the track, but BNSF still owns the mainline. The DMVWR is affiliated with the CP and links into CP lines in central North Dakota. The local railroads are linked to one or the other Class I railroads, and thus provide generally little intramodal competition.

Table 1: North Dakota Railroad Mileage 2011*

Class I	Miles
Burlington Northern Santa Fe	1,714
SOO Line Railroad Company (CP)	482
Subtotal	2,196
Regional Railroads	
Dakota, Missouri Valley and Western	475
Red River Valley and Western Railroad	540
Subtotal	1,015
Local Railroads	
Dakota Northern Railroad	50
Northern Plains Railroad	297
Yellowstone Valley	9
Subtotal	356
Grand Total	3,567

*Figures include trackage rights.
Source: North Dakota Department of Transportation. *North Dakota Transportation Handbook*, 2012, p 23.

Table 2: Railroads Operating in Montana, 2011

Class I	Miles
Burlington Northern Santa Fe	2,003 (157 inactive)
Union Pacific	125
Regional Railroads	
Montana Rail Link	937
Dakota, Missouri Valley and Western	57
Local Railroads	
Central Montana Rail Inc	84
Mission Mountain Railroad	42
RARUS Railway Company	63
Yellowstone Valley	137
Total	3,448

Source: Montana Department of Transportation

Table 3: Kansas Railroad Miles Operated 2011

Class I	**Miles**
Burlington Northern Santa Fe	1,237
Union Pacific System	1,535
Kansas City Southern	18
Subtotal	2,790
Regional Railroads	
Kansas and Oklahoma Railroad	753
Local Railroads	
South Kansas and Oklahoma Railroad	305
KYLE Railroad	417
Cimarron Valley Railroad	183
Nebraska, Kansas, and Colorado Railroad	122
Garden City Western	45
V&S Railway	25
Blackwell Northern Gateway Railroad	18
Blue Rapids Railroad	10
Boothill and Western Railroad	10
Missouri & Northern Arkansas	8
Subtotal	1,143
Grand Total	**4,686**

Source: Kansas Department of Transportation. *2011 Kansas Statewide Rail Plan*, pp 38 and 52.

Unlike Montana and North Dakota, the BNSF and UP have roughly equal track mileage in Kansas (Table 3). The BNSF system is 1,237 miles, or 44%, of the Class I rail mileage while the UP system is 1,535 miles, or 55%, of the Kansas Class I miles. Also, both railroads serve the major Kansas grain storage and marketing centers (Kansas City, Abilene, Salina, Wichita, Topeka, and Hutchinson). Kansas has one regional railroad, the Kansas and Oklahoma, operating 753 miles in central and western Kansas. Kansas has 10 local railroads that collectively operate 1,143 track miles, or about 25% of the total Kansas rail system. The major local railroads are the Kyle (417 miles) serving north central and northwest Kansas, and the South Kansas and Oklahoma Railroad (305 miles) serving southeast Kansas. The local railroads don't compete with UP or BNSF.

Tables 4 through 6 display wheat production for the 2008 to 2012 period by Crop Reporting District (CRP) for Montana, North Dakota, and Kansas, respectively. Between 2008 and 2010, total Montana wheat production increased from 164.7 million bushels to 215.4 million in 2010, a gain of about 30%. In 2011, wheat production plummeted to 175 million bushels, an 18.8% decline from 2010, before recovering to 194.8 million bushels in 2012. The north central and northeast CRDs are the primary wheat growing areas, collectively accounting for an average of 75.7% of Montana wheat production from 2008-2012.

Table 4: Montana Wheat Production by Crop Reporting District (CRD)[1], 2008-2012 (Thousands of Bushels)

CRD	2008	2009	2010	2011	2012	Average[2]
Northwest	2,460	2,169	2,736	2,697	2,416	2,496
North Central	82,665	80,762	97,986	88,852	87,501	87,553
Northeast	37,500	51,845	62,732	43,927	67,846	52,770
Central	20,250	19,414	25,255	18,706	19,228	20,571
Southwest	4,375	4,592	4,877	5,045	3,611	4,500
South Central	10,289	9,608	11,381	10,631	8,557	10,093
Southeast	6,921	7,948	7,339	5,112	5,423	6,549
Other	-	337	3,054	-	168	1,186
Total	164,730	176,675	215,369	174,970	194,750	185,297

[1] Includes spring wheat, winter wheat, and durum wheat.
[2] The column total doesn't exactly equal the corresponding total row column due to rounding.
Source: Montana Department of Agriculture, *Montana Agricultural Statistics*, various issues.

Table 5: North Dakota Wheat Production by Crop Reporting District (CRD)[1], 2008-2012 (Thousands of Bushels)

CRD	2008	2009	2010	2011	2012	Average
Northwest	61,330	75,240	68,133	21,397	74,335	60,087
North Central	32,290	38,190	38,579	22,633	36,363	33,611
Northeast	81,630	66,475	74,045	54,242	69,411	69,161
West Central	14,305	41,400	37,615	20,470	36,755	30,109
Central	30,685	30,540	29,975	17,898	21,843	26,188
East Central	31,535	24,755	27,344	13,920	20,293	23,569
Southwest	15,670	51,290	42,578	22,951	43,320	35,162
South Central	18,730	28,525	24,115	14,708	23,676	21,951
Southeast	25,025	20,145	19,166	11,639	13,215	17,838
Total	311,200	376,560	361,550	199,858	339,211	317,676

[1]Figures include spring, durum, and winter wheat.
Source: USDA; NASS, North Dakota Field Office, Fargo, ND.

Table 6: Kansas Wheat Production by Crop Reporting District (CRD), 2008-2012 (Thousands of Bushels)

CRD	2008	2009	2010	2011	2012	Average
Northwest	37,485	50,400	48,127	40,250	45,040	44,260
West Central	34,475	48,800	53,220	23,550	42,700	40,549
Southwest	45,250	62,250	68,028	32,700	51,270	51,900
North Central	56,215	55,200	50,187	46,550	49,120	51,454
Central	67,360	62,100	55,630	51,270	62,615	59,795
South Central	85,250	70,150	74,267	60,650	92,990	76,661
Northeast	5,860	6,115	4,368.8	4,320	4,720	5,077
East Central	6,480	4,585	1,655.9	5,330	8,885	5,387
Southeast	17,625	10,000	,516.3	11,880	24,860	13,776
Total	356,000	369,600	360,000	276,500	382,200	348,860

Source: Kansas Department of Agriculture, *Farm Facts*, various issues

Table 5 data indicates that North Dakota wheat production rose from 311.2 million bushels to 361.6 million in 2010, an increase of 16.2%. In 2011, wheat production dropped 44.7% relative to 2010 production before recovering to 339.2 million bushels in 2012, an increase of nearly 70% relative to 2011. The northwest and the northeast are the major wheat production regions, collectively accounting for nearly 41% of total North Dakota wheat production during the five most recent years for which data are available.

Table 6 contains Kansas wheat production, which remained relatively steady in the 2008-2010 period, averaging 361.9 million bushels. As was the case for all three states, production plunged to only 276.5 million bushels in 2011, a 23.6% decrease relative to the 2008-2010 average. In 2012, wheat production was 382.2 million bushels, the highest total annual production in the 2008-2012 period and 38.2% higher than 2011 production. The largest wheat producing CRDs are the southwest, north central, central, and south central, that collectively accounted for 68.7% of the average total production during the 2008-2012 period.

The overall objective of the paper is to investigate railroad pricing behavior for the shipment of North Dakota, Kansas, and Montana wheat. Specific objectives include (1) develop a model to measure the impacts of railroad costs and competition on rail wheat rates for North Dakota, Kansas, and Montana, (2) identify and measure the major cost determinants of rail wheat prices, and (3) measure intramodal competition by comparing rail wheat rates in captive markets (Montana and North Dakota) to one with more intramodal competition (Kansas).

Prater (2010) found that in 1988, Montana and North Dakota had the highest rail grain revenue per ton-mile of the 10 major grain producing states. By 2007 this was no longer the case. While there have been many studies of railroad pricing of grain there have been few recent studies comparing variation of regional grain rail rates and the possible causes of the variation. Specifically, there has been no study of rail pricing behavior in the captive rail markets of Montana and North Dakota in the last six years.

LITERATURE REVIEW

Numerous studies discuss railroad industry competition and pricing, providing various degrees of competition within the agricultural industry. Much of the previous analysis investigated the impact of deregulation after the Staggers Rail Act of 1980. However, research interest in the rail industry and competition in the agricultural markets continued up to the present. A significant amount of

the literature is regional in scope motivated by the fact that regional rail transport networks vary, resulting in regional variation in intramodal and intermodal completion.

A large number of studies analyzed changes in agricultural markets following passage of the Staggers Act of 1980. These include Adam and Anderson (1985), Babcock et al. (1985), Chow (1986), Fuller et al. (1987) and Mac Donald (1987), (1989a), and 1989 (b). In general, these studies found that wheat rates declined in all corridors in the 1981-1985 period. Grain rates on movements from the eastern Corn Belt (Indiana, Michigan, and Ohio) increased while rates on movements to the Great Lakes, Gulf of Mexico, and the Pacific Coast declined by large percentages.

Wilson and Wilson (2001) documented the rail rate changes that have occurred as a result of deregulation in the 1972-1995 period. They use a nonlinear regulatory adjustment mechanism to represent the effects of deregulation over time with the largest effects occurring shortly after deregulation. Over time, the total effects of deregulation continue to reduce rail rates but at a slower rate.

The authors found that in 1981, the effect on rates of Staggers was a decrease of 10.6%, 9.9%, 1.8%, 13.7%, and 8.4% for barley, corn, sorghum, wheat, and soybeans, respectively. These initial effects grew over time at a decreasing rate. By 1995, the longer term percent reduction in rates resulting from deregulation was 52%, 46%, 55%, 52%, and 42% for barley, corn, sorghum, wheat, and soybeans respectively. Thus, rail deregulation had relatively small initial effects on rates but eventually converge to larger longer term effects.

Harbor (2008) takes a comprehensive look at competition within the U.S. railroad industry. The author found that the further a shipment originates from water competition, the higher the rail rates. Corn shippers located 100 miles from a barge loading point pay 18.5% higher rates than those located 50 miles from water. Soybean shippers 100 miles from water have rates 13.4% higher than shipments originating 50 miles from barge loading points.

The author concludes that a movement from a monopoly to a duopoly causes corn rates to decline by 23.1% at 25 miles from water, 16% at 50 miles away, and 9.6% at 100 miles from water. A movement from a duopoly to a triopoly causes rail rates for corn to decline an additional 14.2% at 25 miles from water, an additional 10.1% at 50 miles away, and an additional 5.7% at 100 miles.

Some studies have focused on the issue of railroad wheat rates in the northern Great Plains states, especially Montana and North Dakota.

Bitzan et al. (2003) provided insight into inter and intra commodity rail rate differentials observed since rates were deregulated in 1981. The study found that the benefits of rail deregulation are not distributed uniformly across or within commodities, favoring grain producers in regions with higher levels of intermodal competition.

The study concluded that as the number of railroads serving a market decreases or that distance to the nearest water competition rises, rail rates increase. Thus, states dominated by a single railroad and also distant from water competition will have relatively high rail rates. The authors found that the northern, southern, and central plains states had higher rail rates than the Eastern Corn Belt.

Koo et al. (1993) examined railroad pricing behavior in shipping grain from North Dakota to domestic and export destinations by using an econometric technique with cross sectional data from 1984 to 1989.

The authors found that cost factors play an important role in the variation of rates. Distance, volume, and weight per car all have significant effects on North Dakota rail rates. They also discovered that North Dakota's primary commodities (wheat and barley) experience higher rates than corn and soybeans. They said this is the case since wheat and barley are not heavily produced in water competitive regions.

In 2007, Montana lawmakers appropriated $3 million for research into rail issues facing Montana, including rates and service. Cutler et al. (2009) note that Montana is distant from ports and population centers and combined with the bulk nature of the commodities means that motor

carrier intermodal competition is ineffective. Thus, 100% of Montana wheat is shipped by rail to the PNW (Pacific Northwest).

The authors found that in 2006, Montana wheat shippers paid higher average rail rates on a per car basis and a per ton basis than wheat shippers in other nearby states. The same was true for North Dakota. They also found that the average R/VC ratio for Montana wheat shipments to the PNW was 253% in 2006, well above the averages for all other states with significant rail wheat shipments.

However, recent data are inconclusive on whether Montana and North Dakota wheat rail rates are higher than other states. Marvin Prater et al. (2010) examined the sufficiency of rail rate competition in rural areas and the impact of intramodal competition on rail rates. They found that rail competition for grain and oilseeds (soybeans) generally decreased in the 1988-2007 period. Also revenue to variable cost ratios (R/VC) increased in most crop reporting districts (CRD) and the ratios were related to the number of railroads competing in the CRD.

In the 1988-2007 period, Prater et al. (2010) found that in the case of revenue per ton, Montana and North Dakota had the smallest increases of the 10 states evaluated. Iowa, Nebraska, South Dakota, and Kansas had the largest increases.

For revenue per ton-mile, Colorado, Kansas, Indiana, and Missouri had the largest increases, while Montana, North Dakota, and Illinois had the smallest increases. In fact North Dakota revenue per ton-mile actually decreased during the 1988-2007 period.

For (R/VC) ratios, the states with the largest increases were Kansas, Missouri, Colorado, and Nebraska. Montana's ratio remained virtually unchanged. North Dakota and Indiana had the least increase in ratios in the 1988-2007 period.

The USDA (2013) provided average grain and oilseed tariff rates per ton-mile by state, 2006-2010. The study calculated the rates for 36 states. Rates ranged from 2.5 cents (South Dakota) to 9.8 (Michigan). Montana and North Dakota had rates of 3.3 cents and 3.4 cents, respectively. Montana had the 7th lowest rate and North Dakota had the 8th lowest rate. In contrast, Kansas had the 14th lowest rate at 3.7 cents. However, rates are not provided separately for wheat.

MODEL AND DATA

The model is a variant of the model published in Koo et al. (1993). Equilibrium prices of rail transport of agricultural products are determined by the demand for and supply of rail service. Demand for an individual railroad's service (Q_d) is a function of the price of the railroad's service (P_1), the price of other railroads' transport service (P_2, P_3…), the prices of other modes of transport (A_1, A_2…), and other factors affecting the demand for rail transport (S). Thus, the demand function is equation (1).

(1) $Q_d = (P_1, P_2, P_3\ldots, A_1, A_2, S)$.

The supply of a railroad's service is a function of the price of the railroad's service (P_1), the price of other modes transport (A_1, A_2…) and cost factors such as distance (d) and shipment volume (v), and other variables that affect the cost of rail transport (C). Thus, the supply function is equation (2).

(2) $Q_s = f(P_1,\ldots A_1, A_2, d, v, C)$

In equilibrium $Q_d = Q_s$ so equations (1) and (2) can be combined to form the equilibrium condition. Thus, the equilibrium price equation for railroad (1) is as follows:

(3) $P_1 = f\,(P_2, P_3\ldots, A_1, A_2, d, v, S, C)$

If the prices of other railroads (P_2, P_3) are defined as intramodal competition (iac) and the prices of other modes (A_1, A_2...) are defined as intermodal competition (ioc), then equation (3) can be rewritten as follows:

(4) P_1= f (iac, ioc, d, v, S, C)

The empirical model for this study is based on equation (4). As discussed above, intermodal competition is likely to be minimal for rail shipments of North Dakota and Montana wheat. Most of the shipments are long distance movements to Portland, making truck competition ineffective. The average distance from Montana origins to barge loading locations is 522 miles and from North Dakota origins is 421 miles, rendering barge competition to be non-existent. The BNSF dominates the rail industry in Montana and North Dakota, so intramodal competition is non-existent as well. Thus, the empirical model is as follows:

(5) $RATE = B_0 + B_1CARWT + B_2DIST + B_3GVW + B_4BARGE + B_5DUMMY + \varepsilon i$
RATE - Rail rate in dollars per ton-mile for the shipment
CARWT- Weight (lbs) of each loaded covered hopper rail car in a shipment
DIST - Distance in rail miles between origins and export port
GVW - Total shipment weight in pounds (tons)
BARGE - Distance of origin to barge loading facilities
DUMMY - Dummy variable to represent either a Montana or Kansas location, or a North Dakota or Kansas location. Montana or North Dakota are assigned 1 and Kansas 0
ε - random error term

The dependent variable (RATE) is the rail rate per ton-mile and can be obtained by dividing total revenue of the shipment by weight and distance. Calculation is further demonstrated in Table 7. Variation in total revenues of the shipment is obtained by varying the number of cars in the train, and variation in the distance is obtained by varying the origin of the shipment. The total shipment weight (GVW) is obtained by varying the number of carloads in the train and multiplying by the weight per car (CARWT). The distance variable (DIST) is the distance from various origins in Montana and North Dakota to Portland, Oregon, and from various origins in Kansas to Houston, Texas. The distance of the origin to barge loading facilities (BARGE) is the distance from Montana origins to Lewiston, Idaho, the distance from North Dakota origins to Minneapolis, and the distance from Kansas origins to Kansas City, Missouri. Variation in CARWT is introduced by assuming various car sizes, i.e., 268,000-pound cars vs. 286,000-pound cars.

Table 7: Method for Calculation for BNSF Rates Per Ton-Mile

(1)	Total Revenue of Shipment = Number of cars in the shipment x rate per car.
(2)	Weight of the Shipment = Number of cars in the shipment x weight per car.
(3)	Divide (2) by 2,000 to get tons per shipment.
(4)	Divide (1) by (3) to get revenue per ton.
(5)	Divide (4) by distance of the shipment and multiply the result by 100 to get revenue per ton-mile, expressed as an integer.

The theoretically expected sign of the distance variable is negative. A large share of railroad costs are fixed with respect to distance, such as loading and clerical costs, insurance, taxes, interest, and managerial overhead. As these costs are spread over more miles, the costs per mile decrease at a decreasing rate, so the change in the rail rate per ton-mile falls as distance increases.

The GVW variable reflects (a) the number of cars in the shipment and (b) the weight per car. Since the empirical model includes the commodity CARWT, the volume variable reflects the impact on rail rates of increased cars in the shipment. Because a large share of rail costs are fixed with respect to weight, railroads also realize economies of weight. Thus, the change in rail rates per ton-mile are expected to decrease at a decreasing rate as volume increases.

Intermodal competition is proxied by highway miles to barge loading locations. Longer distances to water access points reduce the feasibility of truck-barge competition for rail wheat shipments. Thus, the theoretically expected sign of BARGE is positive since the greater the distance to water ports the greater the pricing power of railroads.

CARWT is expected to have a negative relationship to the change in rail rates per ton-mile. Because operating costs such as switching costs per car, labor costs, clerical costs, and various other costs are fixed per car, these costs per car decrease as car weight increases. Thus the change in rail rates per ton-mile falls as car weight rises.

The empirical model is estimated for Montana, North Dakota, and Kansas. For Montana and North Dakota, the shipments in the empirical model are from Montana and North Dakota wheat origins to Portland, Oregon, for export. For Kansas, the modeled wheat shipments are from Kansas origins to the export ports at Houston. Like Montana, intermodal competition is limited in the Kansas wheat transport market. The distance to Houston makes truck competition nonexistent, and historically only negligible amounts of Kansas wheat have been shipped on the Missouri and Arkansas Rivers. However, unlike Montana and North Dakota, Kansas is served by both the BNSF and UP. The lines of the two railroads are in close physical proximity in many cases, and they have roughly the same number of Kansas track miles (1,237 miles for BNSF and 1,535 miles for UP). Then intramodal competition is introduced by pooling the data of the three states and inserting a dummy variable in the equation for all Montana or North Dakota observations.

The model is estimated using BNSF rates for wheat movements in Montana and North Dakota to Portland and Kansas to Houston. These are believed to be the best data available as it represents accurate BNSF shipping charges as of August 2013. The rates were provided by BNSF personnel for each respective car type and train size. The BNSF personnel also supplied the rail shipping miles from each origin to the port destination.

As Table 8 indicates, the distance from Montana origins to Lewiston, Idaho, range from a low of 410 miles (Collins) to a high of 786 miles (Glendive) with an average distance of 519 miles for the 11 Montana origins. The distance from Kansas origins to Kansas City, Missouri, range from a low of 66 miles (Topeka) to a high of 455 miles (Coolidge) with an average distance for the 10 Kansas origins of 245 miles. The distance from North Dakota origins to Minneapolis, Minnesota, range from a low of 253 (Casselton) to a high of 624 miles (Williston) with an average distance for the 16 North Dakota origins of 437 miles. Thus, Kansas origins are significantly closer to barge loading locations than Montana and North Dakota.

Table 8: Montana, North Dakota, and Kansas Truck Miles to Nearest Barge Facility

Truck Mileage to nearest barge facility – Montana origins to Lewiston, ID			
Glendive	786	Kintyre	678
Harlem	452	Moccasin	463
Collins	410		
Pompeys Pillar	597	Average	
Shelby	449	519	
Carter	413.5		
Rudyard	511		
Grove	467		
Chester	486		

Truck Mileage to nearest barge facility – Kansas origins to Kansas City, MO		
Wichita	197	
Wellington	233	
Salina	183	Average
Hutchinson	223	245
Garden City	387	
Dodge City	345	
Concordia	206	
Abilene	156	
Coolidge	455	
Topeka	66	

Truck Mileage to nearest barge facility – North Dakota origins to Minneapolis			
Grand Forks	313	Scranton	587
Langdon	436	Bernard	352
Casselton	253	Hensler	468
Jamestown	326	Rugby	465
Minot	497	Drayton	357
Bismarck	426	Arvilla	331
Williston	624	Bisbee	459
Bowman	600	Average	
Bottineau	501	437	

EMPIRICAL RESULTS

Table 9 displays the mean, standard deviation, minimum, and maximum values. For the Kansas-Montana model, the mean RATE (revenue per ton-mile * 100) is about 3.5. The mean CARWT is 276,727 with a minimum of 268,066 and a maximum of 286,000 pounds. The mean distance from Kansas origins and Montana origins to Houston and Portland, respectively, (DIST) was about 876 miles with a minimum of 641 and a maximum of 1,214 miles. The mean of GVW (weight of the train) was 19,768,980 pounds with a minimum of 6,164,000 and a maximum of 34,320,000 pounds. The mean of BARGE for truck miles from Montana origins to Lewiston, Idaho, and from Kansas origins to Kansas City, Missouri, was about 435 miles with a minimum of 66 and a maximum 786 miles. The mean of the Montana dummy variable was 0.636.

Table 9 also contains the variable statistics for the Kansas-North Dakota model. The mean of RATE was 3.21 and 275,714 for CARWT. The mean of DIST for wheat shipments from North Dakota origins to Portland and from Kansas origins to Houston was 1,171 miles, with a minimum of 641 and a maximum of 1,602 miles. The mean of GVW was 19,429,930 pounds with a minimum of 6,164,000 and a maximum of 34,320,000 pounds. The mean of BARGE for truck miles from North Dakota origins to Minneapolis and from Kansas origins to Houston was 373 miles with a minimum of 66 and a maximum of 624. The mean of the North Dakota dummy variable was 0.608.

The empirical model was estimated using OLS (robust standard errors) and double log specifications. Equations were estimated for the Kansas-Montana data, the Kansas-North Dakota data, and the Kansas-Montana and North Dakota data for both estimation methods.

For the OLS estimation (see Table 10) of the Kansas-Montana model, CARWT had a positive sign but was non-significant. DIST and GVW had the expected negative signs and were significant at the 1% level. BARGE had the expected positive sign and was significant at the 5% level. The dummy variable was negative and significant at the 1% level, indicating that average Montana wheat rail rates per ton-mile are less than average Kansas wheat rates per ton-mile.

Table 9: Variable Statistics

Montana-Kansas Model Data				
Variable	Mean	Standard Deviation	Minimum	Maximum
RATE	3.498	.0527	2.36	4.8
CARWT	276,727.3	9,012.953	268,000	286,000
DIST	875,765	134,459	641	1,214
GVW	19,768.98	11,350.69	6,164	34,320
BARGE	434.598	167.013	66	7.86
DUMMY	0.636	0.481	0	1
North Dakota-Kansas Model Data				
Variable	Mean	Standard Deviation	Minimum	Maximum
RATE	3.210	0.579	2.36	4.8
CARWT	275,714.3	8,925.925	268,000	286,000
DIST	1,171.216	332.083	641	1,602
GVW	19,429.93	11,741.45	6,164	34,320
BARGE	372.751	135.788	66	624
DUMMY	0.608	0.489	0	1

Table 10: Kansas-Montana Model Results
OLS (robust standard error) Method

Variable	Coefficient	t statistic	p value
CARWT	1.70(e-06)	0.90	0.369
DIST	-.0026422	-8.97**	0.000
CVW	-.0000335	-25.54**	0.00
BARGE	.0005784	2.01*	0.045
DUMMY	-0.18895	-3.3588	0.0011
Constant	5.872175	10.87**	0.000
Observations 264			
F statistic 162.46			
R^2 0.74			
Root MSE 0.269			

**Statistically significant at .01 level.
*Statistically significant at .05 level.

OLS estimation of the Kansas-North Dakota model (see Table 11) found that CARWT had an unexpected positive sign and was statistically significant. As was the case with the Kansas-Montana model, both DIST and GVW had the expected negative signs and were significant at the 1% level. BARGE had an unexpected negative sign and was significant at the 1% level. The dummy variable was positive and significant at the 1% level, indicating that average North Dakota wheat rates per ton-mile are higher than average Kansas wheat rates per ton-mile.

The results of the OLS estimation of the model utilizing the data from all three states are displayed in Table 12. CARWT had the unexpected positive sign but was not significant. DIST and GVW had expected negative signs and the coefficients were highly significant. BARGE had an unexpected negative sign and was significant at the 5% level. The Montana dummy variable was negative but not significant. In contrast, the North Dakota dummy variable was positive and significant at the 1% level.

Table 11: Kansas-North Dakota Model Results
OLS (robust standard errors) Method

Variable	Coefficient	t statistic	p value
CARWT	3.63(e-06)	2.21*	0.028
DIST	-0.0023879	-14.71**	0.000
GVW	-0.0000274	-23.21**	0.000
BARGE	-0.0008152	-5.36**	0.000
DUMMY	0.756382	5.71**	0.000
Constant	5.382395	10.98**	0.000
Observations 245			
F statistic 322.59			
R^2 0.86			
Root MSE 0.2207			

**Statistically significant at .01 level.
*Statistically significant at .05 level.

Table 12: Kansas, Montana, and North Dakota Model Results
OLS (robust standard error) Method

Variable	Coefficient	t statistic	p value
CARWT	2.57(e-06)	1.84	0.067
DIST	-0.0018819	-19.67**	0.000
GVW	-0.0000273	-27.58**	0.000
BARGE	-0.000190	-2.02*	0.045
Montana	-0.07775	-1.59	0.113
North Dakota	0.32917	4.48**	0.000
Constant	5.108501	12.87**	0.000
Observations 245			
F statistic 287.24			
R^2 0.79			
Root MSE 0.24869			

**Statistically significant at .01 level.
*Statistically significant at .05 level.

The empirical results of the double log specification are similar to that of OLS method. The results for the Kansas-Montana dataset are displayed in Table 13. The log of CARWT has a positive sign but is non-significant. Both the log of DIST and GVW have the expected negative sign and are significant at the .01 level. Log of BARGE has an unexpected negative sign but is not significant. The Montana dummy variable has a positive sign but is not significant, indicating there is no difference in average Montana rail wheat rates per ton-mile and average Kansas rates per ton-mile.

Table 14 displays the coefficients and statistical results for the double log specification of the Kansas-North Dakota dataset. Log CARWT has an unexpected positive sign but is non-significant. Both log DIST and log GVW have the expected negative sign are statistically significant at the .01 level. Log BARGE has an unexpected negative sign and is significant at the .05 level. The North Dakota dummy variable has a positive sign and is significant at the .01 level, indicating that North Dakota average rail wheat rates per ton-mile are higher than Kansas average rates per ton-mile.

Table 13: Kansas-Montana Model Results
Double-Log Method

Variable	Coefficient	t statistic	p value
L CARWT	0.116116	0.73	0.464
L DIST	-0.55545	-11.77**	0.000
L GVW	-0.154434	-24.34**	0.000
L BARGE	-0.020705	-1.08	0.279
L DUMMY	0.003313	0.19	0.847
Constant	5.1618	2.57*	0.011
Observations 264			
F statistic 200.94			
R^2 0.72			
Root MSE 0.080			

**Statistically significant at .01 level.

*Statistically significant at .05 level.

Table 14: Kansas-North Dakota Model Results
Double Log Method

Variable	Coefficient	t statistic	p value
L CARWT	0.252022	1.74	0.083
L DIST	-0.7512066	-14.65**	0.000
L GVW	-0.1332539	-24.08**	0.000
L BARGE	-0.276614	-2.03*	0.043
L DUMMY	0.2064771	5.23**	0.000
Constant	4.59084	2.42*	0.016
Observations 245			
F statistic 543.94			
R^2 0.84			
Root MSE 0.070			

**Statistically significant at .01 level.
*Statistically significant at .05 level.

The statistical results for the double log specification of the Kansas-Montana-North Dakota dataset are in Table 15. Log CARWT and Log BARGE both have unexpected signs but neither is statistically significant. In contrast, both log DIST and log GVW have the expected negative signs and are statistically significant. The Montana dummy variable is positive but not statistically significant, indicating no difference in average Kansas rail wheat rates per ton-mile and average Montana rates per ton-mile. However, the dummy variable for North Dakota has a positive sign and is significant at the .01 level. Thus, North Dakota average rail wheat rates per ton-mile are higher than average Kansas rates per ton-mile.

Table 15: Kansas, Montana, North Dakota Model Results
Double Log Method

Variable	Coefficient	t statistic	p value
L CARWT	0.200978	1.72	0.086
L DIST	-0.612514	-18.88**	0.000
L GVW	-0.134345	-28.97**	0.000
L BARGE	-0.004035	-0.32	0.751
MT DUMMY	0.0067543	0.41	0.685
ND DUMMY	0.109476	4.47**	0.000
Constant	4.188548	2.79**	0.006
Observations 413			
F statistic 484.48			
R^2 0.78			
Root MSE 0.074			

**Statistically significant at .01 level.
*Statistically significant at .05 level.

In summary, the results for DIST and GVW were very robust across all six models with the expected negative sign and statistically significant at the 1% level. In contrast, CARWT had the unexpected positive sign in all models but was non-significant in five of the six models. This could be due to a lack of variation in CARWT since the models contained only two car weights (268,000 and 286,000 pounds). Also, CARWT could be correlated with GVW. The empirical results for BARGE were puzzling. It had the expected positive sign and was statistically significant at the .01 level only in the Kansas-Montana OLS equation. In the other five equations, BARGE had the unexpected negative sign and was statistically significant in three cases, and was non-significant in the other two equations.

CONCLUSION

The hypothesis of the paper is that the greater intramodal competition in Kansas compared with the lack of intra-rail competition in Montana and North Dakota would result in higher railroad wheat prices in North Dakota and Montana than Kansas. The empirical results for Montana don't confirm the hypothesis. In the four equations involving Montana data, the dummy variable for Montana is positive but non-significant in two of the four equations and negative but non-significant in another case. In one case, the Montana dummy variable is actually negative and significant, indicating that Montana average wheat rates per ton-mile are lower than those of Kansas.

The empirical results for North Dakota are consistent with the expectation that railroad average wheat rates per ton-mile are higher than average Kansas wheat rates due to greater intramodal competition in Kansas relative to North Dakota. The dummy variable for North Dakota is positive and significant at the .01 level in all four equations involving North Dakota data, indicating higher average rail wheat rates in North Dakota.

The inconsistent results for the BARGE variable permit no conclusion on the impact of intermodal competition on railroad wheat rates per ton-mile in the three states.

Additional research in this area would explore the hypothesis that intramodal competition varies within a particular state. This can be done by measuring intramodal competition by origin county or by origin Crop Reporting Districts (CRD), which are regional groups of five to 14 counties. The Herfindahl Hirschman Index (sum of squared market shares of each railroad in the CRD) would be used to measure rail vs. rail competition. The higher the index the greater the market concentration in the CRD. The maximum value of the index is 10,000 when one firm has a monopoly in the market. The index approaches zero when a market consists of a large number of firms of relatively equal size.

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Factors Contributing to Police Attendance at Motor Vehicle Crash Scenes

by Richard Tay, Lina Kattan, and Yuan Bai

Police attendance at a motor vehicle crash scene is important for investigating the causes of crashes, reducing secondary crashes, managing traffic, and reducing congestion. However, very little research has been conducted to examine the factors contributing to the likelihood of police attendance. This study hypothesizes that the policies of the police services concerned, convenience and comfort, and expectations of injuries or driver violations will increase the likelihood of police attendance at a crash scene. This conceptual framework is supported by the results from fitting a logistic regression model to crash data from the City of Calgary in Alberta, Canada.

INTRODUCTION

Road crashes are a major cause of deaths and injuries in many countries. For example, 2,755 road users were killed and 192,744 were injured in 2007 in Canada (Transport Canada 2010). In the province of Alberta alone, 485 road users were killed and more than 24,530 were injured in over 113,357 motor vehicle crashes in 2007 (Alberta Transportation 2010). In an effort to improve safety and reduce the social cost associated with automobile crashes, many jurisdictions have developed engineering, enforcement, and education countermeasures, as well as plans to improve emergency response. An area of overlap between enforcement and emergency response that has received very little attention in a typical road safety action plan is the role and the importance of police attendance at crash scenes. In the event of an automobile crash, police officers responding to a service call are expected to administer basic first aid until emergency medical services arrive, interview the relevant people involved, gather information, and complete a police report. More importantly, officers are expected to take precautions to prevent further incidents and to manage traffic at the crash site. Despite its importance, police attendance at crash scenes has not received much attention in the road safety and transport economics literature.

According to the Federal Highway Administration (2004), approximately 20% of all incidents are secondary and caused by a previous automobile crash. Police present at a crash scene may help reduce secondary incidents, as one of the duties of the attending officer is traffic control. A less obvious and sometimes overlooked factor is the effect of an automobile crash on traffic congestion. According to the SWOV Institute (2011), congestion cost is about 13%-14% of the total cost of traffic collisions. The ability of the police to clear obstructions and manage traffic contributes considerably to reducing congestion costs. Additionally, the quality of collision reports and the accuracy and completeness of the data collected are expected to improve significantly with police presence at crash scenes. For example, preliminary examination of the data in this study shows that the percentage of missing data is much smaller for many of the contributing factors when police attended crash scenes. Because traffic safety experts, researchers, and policy makers rely on these data there is a need to improve the quality of their collection and reporting as well as identifying the factors which contribute to police attendance at these crashes.

Despite its importance, very little research has been conducted to examine the factors contributing to the likelihood of police attendance at crash scenes. This study develops and tests a conceptual framework to identify these factors and provides evidence-based recommendations to assist police services and transport agencies in managing their policies and optimizing their scarce

resources. Having police attendance at crash scenes results in better traffic management and prevents secondary incidents, contributes significantly to reducing crash severity, and improves the quality of data collection. Therefore, this research contributes extensively to reducing the social costs of automobile crashes and increasing the efficiency of road safety resource allocation. Although the study uses data from Calgary, Canada, the results are relevant to jurisdictions with similar policies.

POLICE ATTENDANCE AT CRASH SCENES

In most jurisdictions, the police have the responsibility to manage traffic incidents and enforce traffic regulations. One of these traffic management responsibilities relates to attendance at vehicle crash scenes to provide emergency services and submit a collision report. For example, the Calgary Police Services policy states that police officers will attend all traffic collisions where there is a report of injury and emergency medical service has been requested, involving property damage only, hit-and-runs, and when they involve criminal code violations. The policy also provides that police will attend crash scenes when the vehicles involved are inoperable, when vehicular traffic is impeded or there is an indication that the person involved in the collision who is reporting the crash is distorting the facts, when police attendance is necessary to keep peace, and when road conditions, types of vehicles involved, or other factors pose a threat to life or create the potential for further property damage.

In addition to the above policy, the executive of the Calgary Police Service has determined that a call for service will be dispatched where none of the above conditions are present but one of the parties insists on police attendance. However, since the call does not meet the response criteria, it will typically be assigned the lowest priority. This policy is consistent with those of many police services, including the Edmonton Police Services, which requires police attendance only when someone has been seriously injured; an individual does not have documentation, including a driver's license, registration or insurance; if it is suspected that the driver is impaired, and if one or more vehicles cannot be driven.

In summary, whether or not the police attend a crash scene is dependent upon the severity of the crash and the likelihood of a criminal offense having occurred. Nevertheless, police officers have a fair amount of discretion in their decisions to attend crash scenes. But, more importantly, police attendance is possible only if notified of a crash by the drivers involved or others at the scene, and an officer decides to go to the crash scene. If no one at the crash scene notifies the police, but later a driver reports it, then the crash is recorded as not attended by the police in the crash database. In addition, if the police are notified but choose not to attend, and one driver subsequently reports it, it is recorded as not attended by the police in the crash database.

Thus, the final outcome on police attendance at a crash scene is determined not only by the officer involved but also by the people present at the crash scene. The actions of these two parties may be influenced by many factors besides the official policy of the police regarding attendance at crash scenes. Therefore, it would be useful to examine whether decisions leading to police attendance at crash scenes are affected by factors like weather and road conditions, time and location of the collision, number of persons or vehicles involved, crash severity, and the characteristics of the road users involved.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

There are many factors that may contribute to decisions of motorists to notify the police of a crash and a police officer's decision not to go to a crash scene. To account for these factors, it is assumed that a motorist will be more likely to call the police to report a crash if the benefit of doing so outweighs the cost. Similarly, it is assumed that a police officer is more likely to go to a crash scene if the benefit of doing so outweighs cost, and that if motorists do not notify the police of a

crash immediately, they may do so subsequently if the benefit of reporting it outweighs the cost. Certainly, many factors affect these costs and benefits. However, the conceptual framework is restricted to those for which data are readily available.

From the sample of policies described in the previous section, it is hypothesized that police attendance at a crash scene is more likely for crashes which involve casualty or injury, hit-and-run, impaired drivers, those who drive at unsafe speeds, and others who act improperly. In addition to their reporting being required by police policies, hit and run (Tay et al. 2008, 2009), speeding (Retting et al. 2008a,b; Tay 2010) and alcohol/drug impairment (Tay 2005a,b,c; Williams et al. 2007) are driving violations that are also associated with high levels of crash severity. Additionally, it is assumed that motorists who have committed violations are less likely to call the police immediately after a crash to request police attendance at crash scenes though other parties may do so. Regardless of violations, motorists present at crash scenes are more likely to call the police if there is an injury or a fatality.

Besides policy related factors, a group of potential factors likely to increase crash severity and the cost of police going to a crash scene are weather related. It is assumed that the disutility, discomfort, inconvenience, and/or costs associated with waiting for police discourage motorists from calling the police unless necessary. Similarly, the cost of police attendance at crash scenes will be high in adverse weather conditions, and adverse weather conditions in turn are expected to affect the frequency and severity of crashes (Barua and Tay 2010, Obeng 2007) as well as the likelihood of hit-and-run accidents (Tay et al. 2009). Accordingly, it is hypothesized that bad weather (snow or rain, relative to clear weather) and poor road conditions (snow covered, relative to dry) will reduce the likelihood of police attendance at crash scenes.

Another potential factor likely to increase the cost of notifying the police about a crash is the cost of police going to a crash scene and the expected severity of the crash at the time of the crash (Kattan et al. 2009, Lee and Abdel-Aty 2005). It is hypothesized that the cost of the police going to a crash scene will increase with the times that are more inconvenient for travel such as peak hours relative to off-peak hours. Moreover, most people prefer traveling during the day and early evening than late night due to physiological and psychological effects of being on the road during those times (Newbold et al. 2005, Tay 2006, 2008). Finally, drivers generally do not like to drive with sun-glare due to both physical discomfort and vision impairment (Mitra 2014, Hagita and Mori 2014). Thus, it is hypothesized that the likelihood of police attendance at crash scenes will be less on weekdays relative to weekends, peak hours and late nights relative to off-peak hours, and when there is sun-glare and at night relative to daylight.

Returning to policies for police attendance at crash scenes, it is noted that the data in police crash reports are collected after decisions have been made to go to crash scenes. Ex-ante, in deciding whether to go to a crash scene, a police officer may develop a prior expectation of the severity of the crash or the likelihood of a violation occurring based on the types and locations of crashes, highway design and traffic control devices there, and the number of people involved in the crash. These factors will also affect decisions by motorists at the crash scene to call or notify the police. Without these calls the police will be unable to go to the scenes of most crashes.

There are several types of crashes that are more likely to result in injury and fatality (Kim et al. 1995, Obeng 2011). For example, for a two-vehicle crash, a head-on crash will result in more severe injury than an angular crash (passing, side-swipe, angle), which in turn would be more severe than a rear-end crash due to a greater speed differential. Hence, it is hypothesized that police attendance at crash scenes is less likely to occur for all other crash types relative to head-on crashes, and more likely to occur for all other crash types relative to rear-end crashes.

Also, several location and highway characteristics affect automobile crash severity (Rifaat et al. 2012, Kim et al. 2006, Lemp et al. 2011). First, a collision occurring at an intersection is likely to be more severe due to a higher chance of it being an angle crash. On the other hand, collisions at non-intersections or mid-blocks are more likely to be side-swiped and rear-end crashes and tend to be

less severe. Additionally, crashes at intersections are also more likely to involve at least one driver violating a traffic regulation, especially failure to yield to traffic. Second, at locations with properly functioning traffic control devices, the likelihood of a driver violation is higher relative to other intersections. If these devices, especially signal lights, are not functioning properly, drivers often will slow down on approaching the site, resulting in lower crash severity. Third, vertical (slope) and horizontal road alignments (curve) affect both the likelihood and severity of crashes because they affect traction, speed and momentum, and sight distances. Also, street lighting provides better visibility for drivers and improves sight distance, which decreases the likelihood and severity of a crash by providing drivers with more time to react and reduce speed. With respect to road class, divided highways usually have higher design standards and posted operating speeds than undivided highways. The higher these speeds the higher the energy involved in collision, which in turn results in more damage or severe crashes. Therefore, it is hypothesized that police attendance is more likely for intersection crashes than in non-intersection crashes, less likely when a traffic control device is not functioning, more likely at locations with alignment issues than on flat and straight roads, less likely on roadways with artificial lights than on unlit roadways, and more likely at a divided highway relative to an undivided highway.

Again, these factors also are likely to influence decisions by motorists to call the police about crashes. For example, motorists involved in crashes are more likely to call the police if a traffic control device is not functioning to establish that the crash was not their fault. To a lesser extent, the same is true of collisions on roads with alignment issues. On the other hand, artificially lit roads, intersections, and divided highways tend to have heavier traffic volumes and thus, have more witnesses to crashes and a higher likelihood that a motorist will call police.

With regard to vehicle influences, there are three factors that may potentially affect crash severity (Yasmin et al. 2013, Obeng 2011). First, if a vehicle in a crash is inoperable, there is a higher likelihood that the crash is severe or may result in casualties, obstruct traffic, and cause congestion. Second, an older vehicle is hypothesized to provide less protection to occupants than a newer vehicle because it may have fewer safety features such as a collision avoidance system, an electronic stability control, side air-bags or seat-belt pre-tensioners. Third, if a crash involves three or more vehicles, it is hypothesized that it is more likely to result in casualties than collisions between two or fewer vehicles, and involve at least one driver who has committed a traffic violation.

Similarly, vehicle-related factors will also influence the decision of motorists to call the police. For example, occupants of an inoperable vehicle are more likely to call the police to the crash scene rather than reporting the crash subsequently. Also, the more the vehicles involved in a crash, the more likely it is that a driver or a motorist at the scene will call the police. Consequently, it is hypothesized that police attendance is more likely when a vehicle is inoperable, more likely when a vehicle involved in a crash is old, and a crash involves three or more vehicles.

Besides roadway and vehicle factors, the last group of variables affecting road safety relates to road user characteristics (Ferguson et al. 2007, Kim et al. 1995). First, the more people involved in a crash, the larger the benefit of having the police at crash scenes because of increased likelihood of needing professional help. Second, there is a common belief among traffic enforcement officers, based partly on evidence, that young males are more likely to be involved in serious crashes, and commit traffic violations in relation to a crash (McCartt et al. 2009, Lewis et al. 2007, Tay 2005d, 2009). Therefore, it is hypothesized that police attendance at crash scenes is more likely when three or more people and young males are involved.

Of note is that the factors contributing to motorists' decisions to call the police and the decision of police officers to go to crash scenes vary and often are interrelated. The analytical framework in this paper presents only a partial view of these complex relationships, and the factors chosen are primarily data driven. Nevertheless, this paper presents a reasonably strong case for the need to examine the different factors contributing to police attendance at crash scenes.

METHOD

Logistic Regression Model

The objective of this research is to determine the factors that contribute to police attendance at crash scenes. Since the dependent variable is discrete and dichotomous in nature, a binary logistic regression is an appropriate technique to use. In this study, the binary response variable, y, is defined as:

$$(1)\quad y = \begin{cases} 1, \text{ if crash is attended by police} \\ 0, \text{ if crash is not attended by police} \end{cases}$$

The logarithm of the odds ratio of a crash scene being attended by police is given by,

$$(2)\quad \ln\left(\frac{P}{1 \quad P}\right) = \beta X.$$

Where, P is the probability of police attendance at a crash site, b is a vector of parameters to be estimated and X is a vector of independent variables. An estimated value of β_i greater than zero indicates that the probability of police presence will increase when variable X_i changes from zero to one, and vice-versa. In addition to the coefficients, it is customary to calculate the odd-ratios of the variables in a binary logistic model. From Eq. (2), the odds-ratio (OR_i) of a variable X_i is equal to $\exp(\beta_i)$ and it ranges from zero to positive infinity. It indicates the relative amount by which the odds of the outcome (police attendance) increase (ORi>1) or decrease (OR_i<1) when the value of the corresponding independent variable (X_i) increases by one unit or changes from zero to one.

Data

The data used in this study to estimate Eq. (2) are from the official crash database maintained by Alberta Transportation. In Alberta, collision data are collected by the Royal Canadian Mounted Police (RCMP) in the rural areas and by local municipal police forces in larger cities like Calgary and Edmonton. The crash records contain common types of information on collisions, including the time, location and severity of collisions as well as data on the driver, crash type, vehicle, environment, and any special road features at the crash location.

To avoid potential confounding factors due to differences across police services, only data from the City of Calgary are used in this analysis. Data from January 1, 2007, to December 31, 2007, were extracted for this study. Of the 44,931 cases reported, 14,588 (32.5%) were attended by police and 30,343 (67.5%) were not attended by police. The full set of the variables fall into six main groups: occurrence day and time, environmental factors, collision characteristics, road and traffic control device characteristics, and occupant and vehicle-related factors. A summary of the variables are in Table 1.

Because most factors are categorical, dummy variables are created for them. In addition, the time of crash occurrence and the age and gender of those involved were recoded into standard categories to facilitate interpretation. For, example, time of crash is recoded as morning peak, off-peak, afternoon peak, evening, and night; while gender and age are recoded as young male, young female, middle-aged male, middle-aged female, senior male, and senior female. In the regression model, one category of each factor is used as the reference and the estimated coefficients are interpreted relative to it.

Table 1: Summary Statistics (Percent Distribution)

Variables	Not Attended	Police Attended
Crash Severity		
Property Damage Only (PDO)	97.6	81.9
Casualty (fatal or injury)	2.4	18.1
Hit and Run		
No	79.0	82.4
Yes	21.0	17.6
Driver/Pedestrian Condition		
Normal	39.6	69.5
Impaired	0.4	9.0
Unknown	60.0	21.5
Speed		
Safe Speed	30.0	37.1
Unsafe Speed	3.5	10.8
Unknown	66.6	52.1
Driver Action		
Proper	3.0	6.5
Improper	34.1	52.2
Unknown	62.9	41.3
Weather Condition		
Clear	59.5	82.2
Rain	1.5	4.0
Snow/Hail	6.7	10.0
Unknown	32.2	3.8
Road Surface		
Dry	49.7	67.3
Wet	4.0	11.2
Ice	13.5	17.7
Unknown	32.9	3.7
Day of Week		
Weekday	29.5	31.7
Weekend	70.5	68.3
Time of Day		
Morning Peak (7am - 9am)	17.6	14.7
Daytime Off-peak (9am - 4pm)	43.9	34.7
Afternoon Peak (4pm - 6pm)	16.1	18.1
Evening (6pm - 10 pm)	11.7	23.0
Late Night (10pm - 7am)	10.6	9.5

Table 1 (continued)

Variables	Not Attended	Police Attended
Natural Light		
Daylight	41.7	43.2
Sun-glare	14.6	25.8
Darkness	2.1	2.6
Unknown	41.5	28.4
Crash Types		
Head-on	0.3	1.2
Angle	5.0	12.5
Rear End	27.3	25.3
Sideswipe	8.2	7.7
Run-off-road	0.2	2.4
Strike Fixed Objects	47.2	36.4
Passing	1.2	2.3
Backing	7.4	2.1
Unknown	3.3	10.2
At Road Intersection		
No	86.9	56.6
Yes	13.1	43.4
Alignment Issues		
No (Straight and Level)	79.6	17.9
Yes (Curve or Slope)	20.4	82.1
Traffic Control Device		
Functioning	20.4	38.7
Not Functioning	59.6	58.0
Unknown	20.0	3.3
Artificial Lighting		
Yes	63.6	68.6
No	36.4	31.4
Road Class		
Undivided One-way	1.6	8.0
Undivided Two-way	11.6	35.9
Divided with Barrier	4.8	33.1
Divided No Barrier	0.7	6.0
Unknown	81.2	17.0
Vehicle Condition		
Reparable	49.8	82.5
Non Reparable	0.1	0.5
Unknown	50.0	17.0

Table 1 (continued)

Variables	Not Attended	Police Attended
Vehicle Age		
< 15 years old	66.1	70.0
> 15 years old	13.4	21.9
Unknown	20.5	8.1
Number of Vehicles Involved		
< 2	97.8	88.7
> 3	2.2	11.3
Number of People Involved		
< 2	60.6	73.1
> 3	39.4	26.9
Age and Gender of People Involved*		
Young Male	22.8	35.0
Middle-Aged Male	30.6	37.3
Senior Male	20.5	21.3
Young Female	15.8	18.3
Middle-Aged Female	22.5	21.4
Senior Female	13.0	10.5
Unknown	20.7	10.1
Note: * total is more than 100% because of multiple persons involved		

RESULTS AND DISCUSSION

The estimation results are in Table 2. In general, the model fits the data very well with a Chi-squared goodness-of-fit statistic of 29.631 and a probability of less than 0.0001, a relatively large pseudo R-square of 0.631 and adjusted count R-square of 0.563, and a very high percent-predicted-correctly (85.8%). Of the 21 factors considered, only artificial lighting had no statistically significant effect, whereas the other factors had one or more categories (or dummy variables) that were statistically significant. More importantly, most of the estimated coefficients had expected signs, providing some support for the proposed conceptual framework.

In terms of impact, crashes involving traffic violations and resulting in casualties have odds-ratios that are relatively high. This is because police attendance at these crashes is mandated by the official policies of the Calgary Police Services. Additionally, multiple vehicle crashes have the highest impact (OR = 6.103) among all the factors examined, ceteris paribus. This result may be because collisions are usually more severe and visible in multiple car crashes. In addition, since more people are involved in such crashes, there is a greater chance that someone will call the police.

Moreover, speeding (OR = 1.559) is substantially less influential than drunk-driving (OR = 5.523) or hit-and-run (OR = 4.971). This result is counter-intuitive because speeding is one of the main causes of serious crashes and it is often targeted in road safety enforcement and publicity campaigns (Tay 2005d 2010, Retting 2008a, b). Contrariwise, the estimated odds-ratio for other improper actions of drivers (besides speeding and drunk-driving) is less than one (OR = 0.871), indicating that police attendance at this type of crash is less likely than at a crash where the driver is driving properly. One possible explanation may be that these improper actions result in minor

crashes, such as failure to yield at uncontrolled intersections in local areas, or failure to signal. It may also be a result of a strong focus by police on drunk-driving and speeding, which results in a lower priority for other improper actions.

In terms of weather and road surface conditions, it is noteworthy that while rainy weather conditions have no significant effect on police attendance at crash scenes, wet roads increase the likelihood of police attendance by 1.779 times, holding other factors constant. This result implies that police are more likely to attend crash scenes soon after rains when the roads are still wet, which is expected because of the higher likelihood of crashes. On the other hand, both snowy weather and snow covered roads have statistically insignificant coefficients and thus are unrelated to police attendance at crash scenes. These results are consistent with the findings from another study (Rahman et al. 2011) that wet roads are associated with more severe crashes in Alberta, whereas snow and icy roads are associated with lower crash severities.

With regard to the time of collision, police attendance at a crash scene is less likely during times of sun-glare (OR = 0.551) and darkness (OR = 0.657), compared with daylight hours. Also, as hypothesized, relative to daytime off-peak hours, police attendance at crash scenes is less likely during the morning peak hours (OR = 0.855) and night-time (OR = 0.870), and 1.952 times more likely during evenings. However, contrary to expectations, police attendance is 1.192 times more likely during afternoon peaks.

As hypothesized, all the other types of collisions, except run-off-the-road collisions, are less likely to be attended by the police compared with head-on collisions. This result is expected because head-on and run-off-the road collisions are the most likely to result in fatalities and serious injuries. On the other hand, rear-end (OR = 0.160) and sideswipe (OR = 0.195) collisions have the lowest likelihoods of resulting in fatalities and serious injuries and thus, also have the lowest likelihoods of being attended by the police.

Since crashes at intersections and road segments with alignment problems often result in fatalities and serious injuries, it was hypothesized that they would result in a higher likelihood of police attendance at their crash scenes. This hypothesis is confirmed by this study's results which show that police are 1.159 times more likely to attend a crash at an intersection relative to one occurring mid-block, and 2.454 times more likely to attend a crash at a road segment with alignment issues compared with a crash on a straight and flat road segment. Similarly, it was hypothesized that crashes on divided roads are more likely to be attended by police because they tend to be more severe. Again, the results show that compared with one-way undivided roads, crashes on divided roads with and without barriers are, respectively, 1.392 and 1.664 times more likely to be attended by police.

As hypothesized, police attendance at a crash scene is more likely if the vehicle is inoperable because of the possibility that it could obstruct traffic. Obviously, an inoperable vehicle is also closely related to crash severity and the possibility of fatality and injury. Hence, it is not surprising that the odds of police attendance is 2.217 times more likely if at least one of the vehicles involved is not operable. Also, it is found that crashes involving newer vehicles are less likely (OR = 0.806) to be attended by police, a result that is consistent with our hypothesis.

Finally, it is found that crashes involving young males are the most likely to be attended by police, while all the other road user groups have estimated odds-ratios that are less than one. It is not surprising that crashes involving middle-aged females have the smallest odds-ratio (OR = 0.671) or are the least likely to be attended by the police. This is because this group is often perceived to be the least likely to be involved in serious crashes or traffic violations (Evans 2004, Tay 2009, 2006).

Table 2: Estimation Results

Number of Observations: 44,931 Share of Cases with Police Presence: 32.5% % Correctly Predicted = 85.8% Adjusted Count R-Square = 0.563 Nagelkerke R-Square = 0.631 Chi-square = 29.631 P-value < 0.0001			
Explanatory Variable	**Coefficient**	**P-value**	**Odd-Ratio**
Crash Severity (Reference: PDO)			
Casualty	1.574	<0.001	4.826
Hit and Run (Reference: No)			
Yes	1.604	<0.001	4.971
Driver/Pedestrian Condition (Reference: Normal Condition)			
Impaired	1.709	<0.001	5.523
Unknown	-1.209	<0.001	0.299
Speed (Reference: Safe speed)			
Unsafe Speed	0.444	<0.001	1.559
Unknown	0.115	0.001	1.122
Driver Action (Reference: Proper Action)			
Improper Action	-0.138	0.048	0.871
Unknown	-0.253	<0.001	0.776
Weather (Reference: Clear)			
Rain	-0.083	0.451	0.920
Snow	-0.111	0.080	0.895
Unknown	-0.354	<0.001	0.702
Road Surface (Reference: Dry)			
Wet	0.576	<0.001	1.779
Ice	-0.068	0.172	0.934
Unknown	-0.956	<0.001	0.384
Day of Week (Reference: Weekend)			
Weekday	-0.089	0.006	0.915
Time of Day (Reference: Daytime Off-peak)			
Morning Peak	-0.157	<0.001	0.855
Afternoon Peak	0.175	<0.001	1.192
Evening	0.669	<0.001	1.952
Night	-0.139	0.007	0.870
Natural Light (Daytime)			
Sun-glare	-0.596	<0.001	0.551
Dark	-0.421	<0.001	0.657
Unknown	-0.542	<0.001	0.581

Table 2 (continued)

Number of Observations: 44,931 Share of Cases with Police Presence: 32.5% % Correctly Predicted = 85.8% Adjusted Count R-Square = 0.563 Nagelkerke R-Square = 0.631 Chi-square = 29.631 P-value < 0.0001			
Explanatory Variable	**Coefficient**	**P-value**	**Odd-Ratio**
Crash Types (Reference: Head On)			
Angle	-0.627	0.001	0.534
Rear End	-1.831	<0.001	0.160
Sideswipe	-1.633	<0.001	0.195
Run-off-road	0.073	0.770	1.076
Strike Fixed Objects	-1.090	<0.001	0.336
Passing	-0.914	<0.001	0.401
Backing	-1.431	<0.001	0.239
Unknown	-0.305	0.115	0.737
At Road Intersection (Reference: No)			
Yes	0.148	0.001	1.159
Alignment Issues (Reference: No)			
Yes (Curve or Slope)	0.898	<0.001	2.454
Traffic Control Device (Reference: Functioning)			
Not Functioning	-0.266	<0.001	0.767
Unknown	-0.979	<0.001	0.376
Artificial Lighting (Reference: No)			
Yes	-0.003	0.928	0.997
Road Class (Reference: Undivided One-way Road)			
Undivided Two-way	-0.714	<0.001	0.489
Divided with Barrier	0.331	<0.001	1.392
Divided with No Barrier	0.509	<0.001	1.664
Unknown	-2.036	<0.001	0.131
Vehicle Condition (Reference: Reparable)			
Inoperable	0.796	0.006	2.217
Unknown	-0.265	<0.001	0.767
Vehicle Age (Reference: >15 years)			
Less than 15 years old	-0.216	<0.001	0.806
Unknown	-1.121	<0.001	0.326
Number of Vehicle (Reference: ≤ 2 vehicles)			
> Three	1.809	<0.001	6.103

Table 2 (continued)

Number of Observations: 44,931 Share of Cases with Police Presence: 32.5% % Correctly Predicted = 85.8% Adjusted Count R-Square = 0.563 Nagelkerke R-Square = 0.631 Chi-square = 29.631 P-value < 0.0001			
Explanatory Variable	**Coefficient**	**P-value**	**Odd-Ratio**
Number of People Involved (Reference: < 2)			
> Three	0.533	<0.001	1.703
Driver Age and Gender (Reference: Young Male)			
Middle-Aged Male	-0.210	<0.001	0.811
Older Male	-0.210	<0.001	0.811
Young Female	-0.288	<0.001	0.750
Middle-Aged Female	-0.399	<0.001	0.671
Older Female	-0.270	<0.001	0.763
Unknown	-0.004	0.966	0.996
Constant	2.268	<0.001	9.658

CONCLUSION

Police attendance at crash scenes is essential to prevent secondary incidents, manage traffic, reduce congestion, investigate crash causes, and collect crash information. Despite these important contributions, the majority of crashes are not attended by police and very little research has been conducted to examine the factors contributing to police attendance at crash scenes. This study finds that crashes involving casualties (fatalities or injuries), hit-and-run, impaired drivers, unsafe speed, run-off-road, older vehicles, inoperable vehicles, multiple vehicles, young males, or many people, as well as occurring at intersections, on roads with wet surfaces, divided roads, and during afternoon peaks or evening hours, are those which increase the likelihood of police attendance. On the other hand, angle, rear-end, side-swipe, passing, and backing crashes and crashes occurring in rain, snow, morning peak, night-time, sun-glare, or weekends, and on roads with icy surfaces, have less likelihood of police attendance.

In addition, this study finds that the percentages of missing data for many important crash contributing factors are much higher for crashes not attended by police, which reduces the completeness and quality of the data, the quality of the analyses using the data, and the quality of road safety investment decisions made. Also, as previously discussed, about 20% of all crashes are secondary incidents caused by previous collisions, and congestion costs constitute about 13%-14% of the total cost of traffic collisions. These social costs are expected to be substantially reduced with police attendance at crash scenes.

Hence, police policies in Calgary must be revised to encourage police attendance at crash scenes, not only for casualty-related crashes and those involving driver violations, but for all crashes whenever feasible and resources are available. Similarly, Alberta's driver handbook should be revised to encourage road users to notify the police of crashes. In addition, an increase in road user education is needed to increase the likelihood of motorists notifying the police of crashes, and a complementary education campaign is needed to increase police officers' awareness of the importance of attending crash scenes, regardless of whether or not injuries or traffic violations are

expected. Finally, road users should be required to provide relevant information in collision report forms before the report can be accepted.

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Richard Tay *graduated with a B.Sc. from Texas Tech University, an MSc from Stanford University and a PhD from Purdue University. His research interests include transportation economics, engineering, policy and planning, with a strong focus on the analysis and prevention of road crashes. Tay serves on the editorial board of several journals, including* Accident Analysis and Prevention, Analytic Methods in Accident Research, International Journal of Transportation, Journal of the Australasian College of Road Safety, Asian Transport Studies, International Journal of Sustainable Transportation, Canadian Journal of Transportation, *and* Journal of Advanced Transportation.

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Book Reviews

Gallamore, Robert E., and Meyer, John R. American Railroads: Decline and Renaissance in the Twentieth Century. Cambridge, MA: Harvard University Press, 2014, ISBN 978-0674725645.

American Railroads: Decline and Renaissance in the Twentieth Century

by Francis P. Mulvey

"American Railroads: Decline and Renaissance in the Twentieth Century" is a must read for anyone who has marveled at the remarkable comeback of the railroad industry in the United States The authors, Robert Gallamore and the late John Meyer, offer a highly detailed, but nonetheless readable, history of American railroading in the 20th and early part of the 21st centuries.

The story of the development and emerging dominance of the railroad industry in America, its role in the settlement of the West, and the predations of some of the "robber barons" has been told many times before, and the authors do not waste time retelling that history. Their focus is on the reactions (often misguided, in their view) to that dominance and how the cures were likely worse than the disease.

"American Railroads" is mostly chronological, but it is also organized along the lines of the factors that played major roles in the decline and rebirth of the industry—legislation and regulation, competition from other modes, passenger train service, and mergers.

The authors, clearly and rightly, identify excessive, if well-intentioned, regulation as the primary factor in the railroad's decline. The second chapter of their book is titled "The Ills of Government Regulation," leaving little doubt as to the thrust of the arguments in the succeeding chapters.

Gallamore and Meyer provide an excellent treatment of the distinction between cost-based and demand-based (value of service) regulatory ratemaking. In doing so, they lay out many of the principles of transportation economics. Indeed, with little additional material, "American Railroads" could serve as a textbook on the subject. Although economic theory prevailed and value of service pricing was adopted, the way it was implemented undermined its success. They point out that the problem with value of service pricing was that it was applied in a rigid manner and did not allow for timely reactions to changing market conditions.

The authors are also critical of the policy of enforced competition. They detail the impact of the rival freight transport modes—trucks and barges. They repeat the oft-noted fact that while railroads invest their own funds in their privately owned rights-of-way, the competing highway and waterway users pay far less than their fair share of the cost of infrastructures they use. They note that while some railroads received land grants, those grants were more than repaid before World War II through 50% discounts on government traffic. They also note that, historically, new modes of transport have generally been favored over the old. As a result, air and highway modes received more public support than railroads.

A large part of the story of railroading in the United States centers on the need to rationalize the system. Yet in the early part of the 20th Century, progressive Republicans like Theodore Roosevelt and William Taft set out to break up the railroad trusts formed by E.H. Harriman and James J. Hill. However, when the United States entered World War I and took over railroad operations, the anti-trust policy was effectively reversed in the interest of serving the needs of the war. It had grown obvious that there were too many railroads, and in the Transportation Act of 1920, which returned operations to the private railway owners, Congress directed the ICC to pursue a merger policy that

would lead to the creation of roughly 20 regional rail networks. Moreover, strong roads would cross subsidize weaker carriers. The plan never gained traction and there were few mergers until the mid-1950s. By 1955, the authors note that there were still 162 Class I railroads—only 26 fewer than in 1920.

Gallamore and Meyer track the long process of industry rationalization that began in the mid-1950s. Through the 50s and 60s, the ICC tended to approve more parallel mergers than end to end ones as it appeared the agency was more interested in cost savings than possible marketing rewards from end-to-end transactions. However, author Gallamore's PhD thesis in 1968 (written under the tutelage of co-author Meyer) found that parallel mergers generally did not yield the cost savings anticipated, and that while end to end mergers might not produce much in the way of cost savings, they were benign competitively and in some cases might contribute to increased rail-to-rail competition.

Gallamore and Meyer offer a detailed description of the Penn Central debacle and Conrail's subsequent success after a rough beginning. By the time of the Penn Central fiasco, it was clear that America's railroads were in financial trouble, especially in the East and Midwest. The authors take the reader through the legislative attempts to salvage the industry—the 3R Act of 1973, the 4R Act of 1976, and finally the Staggers Rail Act of 1980, which largely lifted the yoke of regulation from the railroads.

The authors devote a chapter on how the Class I railroads of today eventually achieved their final shapes and sizes—two in the eastern United States, two in the western United States, two Canadian with substantial U.S. presence and one smaller one in the Midwest. They discuss the problems some of the carriers experienced in consummating the mergers, especially the UP/SP meltdown. Finally, they discuss the proposed CN/BNSF of 2000, the opposition it entailed and the new merger guidelines issued by the STB. The authors predict no additional mergers for the foreseeable future, but do outline what the pros and cons of a transcontinental railroad such as CN/BNSF would have been.

Although the book focuses on freight rail, it does not ignore passenger train services. The authors note that passenger train traffic began to decline in the 1920s and became unprofitable by 1930. The railroads did make an effort to recapture lost traffic with new equipment and higher quality service, and in fact, traffic, especially coach traffic, grew during the 30s. During World War II, rail passenger traffic greatly increased as a result of wartime restrictions on gasoline and rubber consumption, but after 1945 the long-term decline in passenger traffic resumed and accelerated after the introduction of commercial jet aircraft in 1960. The creation of Amtrak in 1970 relieved the railroads of their common carrier obligation to carry passengers. The authors chart Amtrak's progress over the past 40+ years through its series of presidents and controlling legislation. All in all, they conclude that Amtrak is likely more a success for American railroads than a failure. While they believe that the Northeast Corridor should be spun off as a separate entity, they recognize that Amtrak has done remarkably well in holding the cost of operating the rest of the system to a politically acceptable level. Moreover, they believe, along with Don Phillips, that the creation of Amtrak allowed the freight railroads to avoid the disaster of nationalization.

In "American Railroads," Gallamore and Meyer debunk the widely believed myth that railroads are not technologically innovative. They note that railroads have made technical innovations throughout their history. In the authors' view, the most important innovation in railroading in the 20th Century was the replacement of the steam engine with diesel electric locomotives between 1939 and 1959. Without the diesel electrics, the authors believe that the railroads would not have been able to survive the post-WWII loss of traffic to trucks. Innovations in track, car design, braking systems, and operations are also described and discussed in detail. Finally, they also stress the implementation of new telecommunications, train control, and information systems technologies, all of which have greatly enhanced freight rail performance. They end their chapter on technology with a discussion of positive train control (PTC). They explain how PTC works and lay out the

reasons why the railroads are opposed to this "unfunded mandate." However, Gallamore and Meyer are mostly agnostic on this issue.

"American Railroads" concludes with an afterword covering "Future Policies for US Railroads." The authors extol the benefits of private ownership and control in a largely deregulated environment and they warn against increased regulation or government interference in the marketplace for freight transportation. They do, however, note that there are some areas where government involvement is necessary. Specifically they cite the Section 130 funding for grade crossing warning systems, tax credits for participation in public/private partnerships, subsidized loans for shortlines, and for projects of national significance such as the Alameda Corridor and the CREATE project in Chicago. They also note that the transportation environment is again changing with the decline of coal traffic and the emerging regulation of greenhouse gases. These changes could simultaneously benefit and challenge the railroad industry. On balance, Gallamore and Meyer conclude that laissez-faire is good policy except in rare instances.

Although the book offers an accurate and analytical treatment of the railroad's decline and ultimate resurrection, the discussion of the legitimate role of government in protecting shippers and the public at large from potential monopolistic abuses could be more balanced. Moreover, they do not cite the dramatic changes in the regulatory framework at the STB following Staggers. Also, while the treatment of railroad mergers in the 20th Century is probably the best ever done, the authors say relatively little about the problems that plagued the Norfolk/Southern and CSX railroads following their acquisition of most of Conrail. Finally, while "American Railroads" has an excellent notes section, it could be made more useful to someone interested in the subject with an index that included the names of historical key players. These minor criticisms aside, the book's contribution to a more complete understanding of American railroad history cannot be overstated.

Francis P. Mulvey*, now with ITER Associates, served on the Surface Transportation Board from 2004 to 2013 as board member, vice chairman, and acting chairman. Before joining the STB, Mulvey was staff director of the Railroad Subcommittee of the House Committee on Transportation and Infrastructure. He held previous positions with the US DOT Office of the Inspector General, the former U.S. General Accounting Office, the Transportation Research Board, and the American Bus Association. Mulvey holds a PhD in conomics from Washington State University, a BS in Economics from New York University, and an MA in economics from the University of California at Berkeley. Currently he serves as Vice President Programs-Elect of TRF.*

Macharis, Cathy and Melo, Sandra (eds). City Distribution and Urban Freight Transport: Multiple Perspectives, Cheltenham, UK: Edward Elgar Publishing Limited, 2011, ISBN 978-0-85793-2747.

City Distribution and Urban Freight Transport: Multiple Perspectives

by Anthony M. Pagano

A big problem in major cities across the world is urban goods distribution. We have all experienced congestion, pollution, and the blockage of streets as trucks attempt to deliver goods to retail establishments in the heart of the city. This book,edited by Macharis and Melo, is the source for a rich series of articles concerning methods of attempting to deal with this problem. The urban goods distribution problem is not new. In the early 1900s, Chicago built a series of railway tunnels under State Street and other downtown streets to provide delivery of coal and goods to local retailers. These abandoned tunnels were destroyed during the Great Chicago Flood of 1992.

The series of articles in this book are all written by researchers in Europe. European cities have many more problems of urban goods distribution than in the United States. Most of these cities started out as walking cities with narrow cobblestone streets suitable only for people and horses. Trying to fit delivery vehicles into these streets creates many of the problems addressed in this book. The book is divided into three major parts. Part I defines the urban goods problem and possible solutions. Part II examines possible methods to deal with the problem, while case studies in different European cities are the subject of Part III.

Laetitia Dablank is the author of the first chapter. She discusses the major changes in cities in developed countries that have aggravated the urban goods distribution problem. For example, store inventories have shrunk, and businesses are increasingly supplied on a just-in-time (JIT) basis. Moreover, the number of different products sold has increased, and collections change several times per year. Express and courier services are increasing. She notes that urban freight emits far more pollution that long-distance freight because the vehicles are, on average, older; there are many stops and short trips.

A variety of possible solutions are discussed throughout the book. These include Urban Consolidation Centers (UCC), which have been implemented in Japan and a few European cities. In these UCC's, goods are delivered to a central location near the city, then consolidated deliveries are carried to individual retailers in the heart of the city. Other solutions include bans on very large trucks in the city center, bans on older, more polluting delivery vehicles, promotion of night deliveries, delivery time window restrictions, parking and unloading regulations, and road pricing. Each of these solutions has positives and also many negatives. H.J. (Hans) Quak also mentions company driven initiatives, which include carrier cooperation, vehicle routing improvements and less polluting vehicles. He notes that despite all these initiatives, "great breakthroughs have not been made."

One interesting idea is the Limited Traffic Zone (LTZ), which was implemented in the historic center of Rome. This is a series of regulations concerning time windows for goods and passenger vehicles. Fees are imposed for entry to the Zone and are reduced for least polluting vehicles. In Chapter 4 of the book, Stathopoulus, et al. describe a series of focus groups with stakeholders to identify problems with the LTZ. Stakeholders include Rome's industrialist and enterprise associations, carriers, and local public authorities. Among the problems identified are conflicting objectives among stakeholders regarding traffic flows and parking.

The conflicting views of stakeholders is the subject of the chapter written by Macharis, et al. Their analysis shows that different stakeholders have different views as to what is the most desirable approach to dealing with urban freight problems. This clash of viewpoints means that reaching a consensus on what to do is quite difficult, if not impossible, in urban areas.

The approaches taken by a number of European cities are dealt with in the remaining chapters of the book. This includes a description of the "Padua Model," which has been implemented in several cities, and the systems in the Italian cities of Lucca, Parma, and Venice, which has its own unique urban delivery problems. Van Lier and Macharis examine the case of Brussels, which uses the port of Brussels and inland waterways to do part of the transportation. Maes and Vanelslander describe the system used by the French retail group Monoprix. The company ships by rail to a downtown logistics center in Paris. From there, the last mile is accomplished by natural gas powered trucks. Menge and Hebes describe a courier, express, and parcel service project in Berlin. They note that up to 35% of urban goods traffic is generated by these services.

Sandra Melo, one of the book's editors, describes and evaluates possible goods distribution systems in Porto, Portugal. This chapter is part of her Ph.D. dissertation. She utilizes a set of indicators to evaluate the different systems. These include delivery times, operational costs, emissions, average speed, and others. She concludes that local administrators, supported by planners and consulting the main stakeholders involved, can significantly contribute to good practice in urban goods movement.

This book provides quite an array of articles on many facets of urban goods distribution. Almost all the research cited and all the authors are European. This reflects the fact that urban goods distribution is a serious problem in compact European cities. In addition, most of the work done in this field has been accomplished by European or Japanese researchers. The United States has lagged behind in research in this field and implementation of ways of dealing with it. Part of the reason is that many U.S. cities were developed as the automobile grew in importance and so this problem is not as severe in these cities as those in Europe. But there is much we can learn from this book about the state of the art. Unfortunately, because there are so many stakeholders involved and many tradeoffs, solutions to the urban goods distribution problem will always be elusive.

Anthony M. Pagano *is director of the Center for Supply Chain Management and Logistics at the University of Illinois at Chicago. He has served as president of the Transportation Research Forum and co-founder and co-general editor of the Journal of the Transportation Research Forum. Pagano teaches courses in transportation economics and logistics. His PhD is in economics from Pennsylvania State University.*

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.

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2007	John (Jack) V. Wells
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2005	Scott E. Tarry
2004	John S. Strong
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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)
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ISSN 1046-1469

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