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On the cover: All the major airlines were forced to develop strategies to cope with the post-9/11 environment in order to survive. In "An Analysis of a Strategic Transformation Plan: The Case of Alaska Airlines," Paul Caster and Carl Scheraga empirically assess the effectiveness of Alaska Airlines strategy.

BOOK REVIEWS

A Message from the JTRF Co-General Editors

The Spring 2013 issue of *JTRF* contains the usual wide variety of contemporary transportation topics that is the distinguishing characteristic of *JTRF*. Topics in this issue include the following:

- Injury severity of young drivers
- Airline strategy
- Airport efficiency
- Fatigue-induced collision risk of transit bus operators
- Truck use on Texas toll roads
- Exhaust emission and fuel economy
- Gate violations at highway-rail grade crossings

In "Modeling Injury Severity of Young Drivers Using Highway Crash Data From Kansas," Niranga Amarasingha and Sunanda Dissanayake investigated characteristics and contributory causes of young-driver crashes and developed multinomial logit models to identify severity affecting factors. The authors' objectives were to investigate the characteristics and contributory causes by numbers and percentages, crash rates, and crash-severity factors related to highway crashes involving teen and young-adult drivers in Kansas. The authors found that teen drivers were more likely to be involved in crashes due to failure to give time and attention as well as falling asleep. They also found that alcohol involvement, not wearing seat belts, driving without a license and involvement with off-road crashes were factors that increased young driver injury severity.

Paul Caster and Carl Scheraga assess Alaska Airlines' 2010 strategic transformation in "An Analysis of a Strategic Transformation Plan: The Case of Alaska Airlines." To do this the authors employ strategic variance analysis (SVA). SVA is used to analyze a company's profitability by breaking it down into strategic components including cost leadership, product differentiation, growth, and capacity underutilization. The authors found that Alaska Airlines focused primarily on growing its share of the market and on productivity gains by cutting costs. They also made changes in their routes to achieve better use of capacity. The authors found that by 2009 Alaska ranked first in both productivity and price recovery, and third in market share growth.

In "Efficiency Benchmarking of North American Airports," Zhuo Lin, Yap Yin Choo, and Tae Hoon Oum use three different methods to examine the efficiency performance of 62 Canadian and U.S. airports. The methodologies employed by the authors include the productivity index method, the Data Envelopment Analysis (DEA) method, and the stochastic frontier analysis (SFA) method. The authors use a comprehensive output measure that includes both aeronautical and non-aeronautical service outputs. The data set consists of a cross section of 55 U.S. and seven Canadian airports in 2006. The authors found the efficiency scores and rankings measured by the three alternative methods are quite similar in the top 15 and bottom 15 ranked airports, whereas considerable differences exist among airports in the middle range. The authors also found that the percentage of non-aeronautical revenue, passenger volume, average aircraft size, and percentages of international and connecting traffic significantly affect the efficiency estimates of all three alternative approaches.

Enock T. Mtoi, Ren Moses, and Thobias Sando explore the relationship between fatigue-induced crash risk, transit operator hours of service, and fatigue management policies in "Modeling Fatigue-Induced Collision Relative Risk: Implications of Service Hours and Fatigue Management Policies on Transit Bus Operations in Florida." The objective of this study is to analyze bus operator hours-of-duty policies in Florida and determine if there are safety impacts that may prompt changes for these policies. The authors use incident reports and operator schedule data archived by transit agencies to determine the relationship between crash involvement and operator schedules, using logistic regression. Regression results revealed a decreasing trend of collision risk when drivers start their schedules in the late morning or in the afternoon compared to early morning. The authors found increasing collision risk for driving long hours without enough off-duty time. They also found that drivers who work split-shifts have higher relative crash risks than drivers who work straight-runs.

In "Truck Use on Texas Toll Roads," Dan Seedah, Joshua Muckelston, and Robert Harrison examine the current failure of Texas toll road SH-130 to attract truckers from IH-35 in Austin, one of the most congested Texas corridors. The objective of the study is to introduce a methodology that can be used to estimate truck operating cost over any user-defined route profile. The authors also present a case study that illustrates how planners and toll entities can determine which routes trucking companies will choose based on factors such as distance, travel time, congestion levels, travel speeds, toll charges, and pavement conditions. The authors achieve the objective by developing CT-VCOST, a comprehensive vehicle operating cost toolkit, which can be used to calculate truck operating cost on both SH-130 and IH-35. The results indicate why few truckers are using the toll facility.

Jun Tu, Scott Wayne, and Mario Perhinschi use correlation analysis to investigate the effects of drive cycle characteristics on distance-specific emissions and fuel economy in "Correlation Analysis of Duty Cycle Effects on Exhaust Emissions and Fuel Economy." The purpose of the paper is to investigate the drive effects of cycle characteristics, or metrics based on second-by-second vehicle speed data, on distance-specific emissions in order to identify the most important parameters to be included in a predictive emissions model. This information is used as an input to bus procurement decisions. The authors found that average speed, number of stops per mile, percentage idle, and kinetic intensity were the most important cycle metrics affecting emissions and fuel economy.

In "Gate Violations by Truck Drivers at Highway-Rail Grade Crossings in Two Cities," Aemal Khattak investigated gate violations during train crossing events by truck drivers at highway-rail grade crossings in two Nebraska cities. The methodology consisted of collecting data at two gated highway-rail crossings where truck drivers were observed during train crossing events. The data was statistically analyzed to assess the prevalence of gate violations by truck drivers. The author found that the frequency of violations increased with higher truck traffic during crossing events, and drivers of single unit trucks had a greater propensity for gate violations compared to drivers of trucks with trailers. Also he found that violations were more frequent with longer times between the onset of flashing lights and train arrivals at crossings.

Michael W. Babcock
Co-General Editor

Kofi Obeng
Co-General Editor

Modeling Injury Severity of Young Drivers Using Highway Crash Data from Kansas

by Niranga Amarasingha and Sunanda Dissanayake

Young drivers have higher motor vehicle crash rates compared to other drivers, and understanding the reasons for this would help to improve safety. This study, therefore, investigated characteristics and contributory causes of young-driver crashes and developed multinomial logit models to identify severity affecting factors. It was found that teen drivers were more likely to be involved in crashes due to failure to give time and attention and falling asleep. Among other factors, alcohol involvement, not wearing a seat belt, driving without a valid license, having restrictions on driver's license, and involvement in off-roadway crashes were factors that increased young-driver injury severity. Based on identified factors, countermeasure ideas for improving safety have also been suggested.

INTRODUCTION

Teen and young-adult drivers have much higher motor vehicle crash rates per licensed driver than other drivers, both in Kansas and throughout the United States (U.S.) (Ballesteros and Dischinger 2002). The higher crash propensity among young or beginning drivers may result from lack of driving experience and their risk-taking behavior. Motor vehicle crashes are the leading cause of death among young drivers in the U.S. (IIHS 2008). National statistics in 2008 showed teenage drivers accounted for 12% of all drivers involved in fatal crashes and 14% of all drivers involved in all police-reported crashes but they accounted for less than 5% of all drivers (IIHS 2008, USDOT 2008). Also, beginning drivers were three times more likely to die in a motor vehicle crash than an average driver (IIHS 2008). In Kansas, the young-driver safety issue has been identified by the Kansas Strategic Highway Safety Plan as one of the major concerns that leads to increased fatalities and serious injuries (KDOT 2010). Hence, it is important to investigate characteristics and contributory circumstances related to young-driver crashes and associated severities while identifying over-represented factors. Such results can be used to recommend better crash mitigation strategies, thereby improving the safety of young drivers.

Accordingly, the objectives of this study were to investigate the characteristics, contributory causes by numbers and percentages, crash rates, and crash-severity factors related to highway crashes involving teen and young-adult drivers by investigating coefficient estimates through development of a multinomial logit model. Crash rates were calculated in terms of crashes per 1,000 drivers and Vehicle Miles of Travel (VMT). Comparisons between teen drivers, young-adult drivers, and experienced drivers were also carried out in order to identify young-driver over-representation in various crash characteristics and contributory causes of young-driver-involved crashes.

LITERATURE REVIEW

High crash rates by young drivers are well documented in the literature, whichever exposure data (e.g., number of licensed drivers, vehicle miles travel) are used in calculating the rates. In Maryland, for example, the youngest drivers have been found to have the highest rate of motor vehicle crashes per licensed driver and per annual miles driven (Ballesteros and Dischinger 2002). In particular, young drivers have greater risk of crashes than their older counterparts. Numerous contributory factors have been related to crash risk of young drivers such as risk-taking behavior, nighttime driving, driving with young passengers, and being under the influence of alcohol (Fu and Wilmot 2008). Inattention and distraction were also identified as critical factors that increase injury severity of young drivers involved in motor vehicle crashes (Neyens and Boyle 2007). Many studies have focused on young-driver crash involvement and crash risk. Based on the study conducted in Louisiana using crash data from 1999 to 2004, young driver risk-taking behavior was much more present in male drivers with the presence of male peers than the female-to-female, driver-passenger combination (Fu and Wilmot 2008). The risk of being involved in a fatal crash was much higher for teenage drivers when passengers were present. Cooper et al. (2005), using fatality and crash data from 1991 to 1997, studied the new passenger restrictions in California, which are that new provisional license holders are restricted from transporting those under 20 years old for the first six months. The law has been effective in reducing these rates, and the reduction of passengers in crash-involved cars resulted in an estimated saving of eight lives and 684 injuries over three years. Hanna et al. (2006) investigated young unlicensed drivers' involvement in fatal crashes, using data from Fatality Analysis Reporting System (FARS).

Young unlicensed driver involvement in fatal crashes was similar to young licensed drivers' involvement in fatal crashes. However, the errors for experienced young drivers were relatively few in number and small in magnitude, according to the study conducted in California from 1996 to 2000 by McKnight and McKnight (2003). Benefits of experience apply rather generally across all aspects of driving, as behavioral shortcomings such as failure to employ routine safe operating practices, failure to recognize danger, and risk-taking are high in beginning drivers. A logit model of teen-driver injury crashes, which was developed by Vachal and Malchose (2009), using crash data from 2001 to 2007, offered insight for creating a safer driving environment for teen drivers. They found that increased licensing age and seat belt emphasis might reduce teen traffic injuries. The risk attached to lower age, lack of seat belt use, and impaired driving is evident. Also, gender is a factor in teen-driver injury severity, with females at higher risk. For several years, many efforts such as the introduction of graduated licenses have been focused on reducing young-driver crash involvement in the U.S. It has resulted in some progress nationally in reducing fatal crashes among 16 year olds but young drivers' over involvement in crashes was still a big problem (Williams, Ferguson, and Wells 2005). Gonzales et al. (2005) studied 16-year-old drivers involved in fatal vehicle crashes during 1995-2000 and compared them with fatal-crash-involved experienced drivers with respect to characteristics and driver behaviors. According to the study, new drivers must be given a top priority to improve traffic safety as they bear considerable responsibility for fatal crashes.

Numbers of young-driver-related studies have used state-level databases or national-level databases such as FARS and the General Estimate System (GES). Also, many research studies have focused on young-driver crash involvement and crash risk. Most of the preliminary analyses were done using the absolute number of crashes at each age*,* frequencies, percentages, and Pearson Chi-Square tests (Hanna et al. 2006; McKnight and McKnight 2003; Williams, Ferguson, and Wells 2003). Second, more comprehensive analyses such as multiple logistic regression and multiple probit analyses were done to check the association between driver injury severity and related factors. For example, binary logistic regression models were developed to compare teen drivers and experienced drivers in Colorado using FARS data (Gonzales et al. 2005). In order to investigate the crash severity of young-driver crashes, Dissanayake and Lu (2002) developed a sequential binary logistic regression model using the Florida traffic database. Crash severity was defined under five categories: no-injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury. Neyens and Boyle (2007) used GES data, which contain both teenage drivers and their passengers, to develop an ordered logit model. The dependent variable, which was injury severity, was also defined under five categories. Results showed that teen drivers have an increased likelihood of more severe injuries if distracted by a cell phone or passengers than other sources of distraction. Using injury crash records, a multinomial logit model was developed to study driver, vehicle, and road-related factors for North Dakota teenage drivers (Vachal and Malchose 2009). The relative likelihood of severity, which is driver fatality or disabling injury, in a crash was the dependent variable.

Mercier et al. (1997) assessed whether age and gender, or both, influenced injury severity in head-on automobile collisions on rural roads. Data were obtained from Iowa Department of Transportation's Accident File, beginning from 1986 through part of 1993. All the collisions could be divided into three groups; head-on, broadside, and angle approach. Since the head-on collisions were the most severe crashes, the study was limited to those crashes. Also, this study limited for crashes on paved surfaces, and front seat occupants. The principal components logistic regression and hierarchical logistic regression models were developed using injury severity as the dependent variable, which was measured as fatal, major, or minor. In the preliminary analysis, 14 independent variables were considered. Results showed that age remains as a very important factor for predicting injury severity. The deployed air bags seemed more beneficial for women than for men, whereas use of lap and shoulder restraints appeared to be more beneficial for men. This study recommended reexamining the design parameters for protective systems in automobiles.

Aldridge et al. (1999) investigated the effect of passengers on young driver accident propensity using crash data that were extracted from a Kentucky accident database between 1994 and 1996. In this study, young drivers were individuals between the ages of 16 and 20 years and peers to these young drivers were individuals between 12 and 24 years old. The analysis was done using the induced-exposure technique, which measures the Relative Accident Ratio (RAIR) by taking the ratio of the percentage of at-fault drivers in a specific subgroup to the percentage of not-at-fault drivers for the same subgroup. Seven possible interaction variables, driver gender, total occupant gender, time of the week, time of the day, vehicle age, and safety restraint usage were considered. Young drivers have a high propensity for causing single-vehicle crashes when traveling with peers, but they have lower propensity to cause either single-vehicle crashes or multi-vehicle crashes when traveling with adult/child passengers. These findings of this study supported for the Kentucky's graduated license program. Further, it suggested increased education and a training period for young drivers under adult supervision.

Despite these suggestions, young drivers still have higher crash rates compared with other drivers. Using a multinomial logit model, this study compared the young drivers' crash rates for each characteristic with experienced drivers' crash rate that may add new information to the young driver safety literature. Also, no research has been done to investigate young driver safety issues using Kansas crash data.

Kansas Law Related to Young Drivers

The Kansas law prior to 2010 covering licenses is summarized in this section (KDOT 2009). The minimum age to obtain an instruction permit in Kansas was 14 years, with the requirement of adult supervision at all times. Restricted licenses were issued at 15 years with only driving to, from, or in connection with any job- or employment-related work or school allowed. Even then, the most direct and accessible route between the driver's home and school or work was to be used. However, a restricted license holder could drive anywhere, anytime with a licensed adult driver's supervision. Passenger restrictions included transportation of non-sibling minor passengers. At age 16, a full license was granted if a 50-hour affidavit, which is proof of completion of 50 hours of driving, had been turned in. The law changed in 2010 with the current law allowing fewer restricted licenses at age 16 instead of a full license, and after six months a full license is granted. Even though the law changed in 2010, it did not have any effect on this study because all data for this analysis were from the period before the law changed.

In Kansas, the minimum age to have a restricted license was 15 years. Most of the past studies which focused on young drivers commonly investigated the age limit from the time the restricted license was granted to 25 years (Ballesteros and Dischinger 2002; McKnight and McKnight 2003).

This age range shows similar driving behavior and crash risk (KDOT 2010). Hence, in this study the range of young drivers considered was from age 15 to 24. In order to investigate young-driver characteristics in detail, they were further divided into two groups: the teen-driver group from age 15 to 19 and the young-adult-driver group from age 20 to 24. In order to compare young-driver characteristics with other driver characteristics, all middle-age drivers in Kansas were taken into account. Those middle-age drivers were defined as “experienced drivers” whose ages ranged from 25 to 64 (Ballesteros and Dischinger 2002; Gonzales et al. 2005). Those above age 65 were not considered to compare with young drivers because older-driver characteristics may be different from those of 25- to 64-year-old drivers, and older drivers have also been found to have unique highway safety challenges (Gonzales et al. 2005; Kostyniuk and Shope 2003).

DATA AND METHODOLOGY

Data

Crash data from 2006 to 2008 were obtained from the Kansas Department of Transportation (KDOT). This data set, Kansas Accident Reporting System (KARS) database, comprises all police-reported crashes that have occurred in Kansas. Motor vehicle young-driver-involved crashes on highways were taken into account, excluding motorcycle and motor scooter crashes. The KARS database from 2006 to 2008 contained 94,817 (30% of total crashes) young-driver-involved crashes and 186,600 (58% of total crashes) experienced-driver-involved crashes. Driver contributory factors for 54,349 crashes were recorded for the 94,817 young-driver-involved crashes. There were up to 10 contributing factors recorded in the traffic crash database for some crashes, while contributory factors were not recorded at all in some other crashes. Environment-related contributory causes were recorded for 636 crashes involving teen drivers, 527 crashes involving young-adult drivers, and 1,867 crashes involving experienced drivers.

Crash Rates

In order to calculate crash rates, driver’s license information for each year by age was obtained from the U.S. Department of Transportation (USDOT 2008; USDOT 2007; USDOT 2006). Table 1 provides the number of licensed drivers in Kansas during 2006 through 2008 by age group and gender. From 2006 to 2008, the number of licensed teen drivers increased from 159,655 to 166,663, and the number of licensed young-adult drivers increased from 177,407 to 181,616 in Kansas. However, the number of experienced drivers dropped from 1,361,297 to 1,343,497. Vehicle Miles Traveled (VMT) was calculated using from National Household Travel Survey (NHTS) data for the Midwest region, because the sample size for Kansas was too small (NHTS 2009). The Midwest region consists of Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota, and Wisconsin. Annualized travel day VMT by each age for the Midwest were extracted from the NHTS database (NHTS 2009). This gives the average VMT by the interviewed drivers in each age, and the VMTs were divided by the respective sample size to obtain VMT per driver. The VMT per driver were categorized for each age group. Then multiplying those values by the number of Kansas drivers in their respective age group, the total annual VMT by Kansas drivers in each age group was estimated. Estimated Kansas VMT for teen, young-adult, and experienced groups were 920, 1,724, and 17,750 million per year, respectively (NHTS 2009). Those values were then multiplied by three in order to obtain total VMT for three years. The crash rates per VMT were calculated for each age group by dividing the number of crashes of age group by VMT of respective age group.

Table 1: Number of Licensed Drivers in Kansas

Driver Category		2006	2007	2008
Teen (15-19)	Male	81,815	83,689	85,138
	Female	77,840	80,033	81,525
	Total	159,655	163,722	166,663
Young-adult (20-24)	Male	89,475	91,088	91,788
	Female	87,932	90,084	89,828
	Total	177,407	181,172	181,616
Experienced (25-64)	Male	681,280	679,586	698,566
	Female	680,017	675,804	1,397,132
	Total	1,361,297	1,355,390	1,343,497

Source: USDOT 2008; USDOT 2007; USDOT 2006

Multinomial Logit Model

A multinomial logit model was developed to identify variables expected to have an explanatory effect on injury severity of young drivers involved in crashes. Using the coefficient of the explanatory variables, risk factors that increase young-driver injury severity could be determined. The dependent variable, injury severity, has several discrete categories. The dichotomous nature of the dependent variable facilitates the application of logit analysis, for which the probability of fatal injury against other injury-severity categories is estimated by the maximum likelihood method (Long 1997). The probability of driver n being injured with severity outcome *i* is

(1) $\Pi(x)_{ni} = P(U_{ni} \geq U_{ni'}), \quad \forall' \in I, \quad i' \neq i,$

where,

$\Pi(x)$ = the probability of x injury category,
n = a driver,
i = the injury severity of n driver (e.g., fatal injury, incapacitating injury, minor injury, no
injury),
U_{ni} = a function determining injury severity outcome i of the n driver,
$U_{ni'}$ = a function determining injury severity outcome i' of the n driver, and
I = a set of I possible, mutually exclusive severity categories.

The logit model assumes a driver-injury severity function has a linear-in-parameters form as

(2) $U_{ni} = \beta_i x_n + \varepsilon_{ni}$

where

β_i = a vector of estimable coefficients for injury severity i and x_i is a vector of variables for driver n; and
ε_i = a random component which has identically and independently distributed error terms.

Then the multinomial logit model is defined as follows (Long 1997):

$$(3)\quad \Pi(x)_{ni} = \frac{e^{\beta_i x_n}}{\sum_{\forall i' \in I} e^{\beta_{i'} x_n}}$$

The maximum likelihood method is then used to estimate the coefficients.

In some cases, logistic regression results may seem paradoxical, which means the model fits the data well, even though none of the independent variables has a statistically significant impact on predicting the dependent variable. This has happened due to the correlation of two or more independent variables. Neither variable may contribute significantly to the model after the other one is included. However, model fit will be worse if both variables were removed from the model. This is because the independent variables are collinear and the results show multicollinearity. In traffic safety analysis, the goal is to understand how various independent variables impact the dependent variable; hence, multicollinearity is a considerable problem (Motulsky 2011). One problem is that even though the variable is important, model results show it is not significant. The second problem is that confidence intervals on the model coefficients will be very wide. To help assess multicollinearity, the correlation matrix of the independent variables was investigated. If the element of correlation matrix has high value, model fit is affected by multicollinearity of the independent variable correspondent to that element. Also, each independent variable can be predicted from other independent variables. The model-fit statistic such as individual R^2 value and a variance inflation factor (VIF) are high for any of the independent variables, and model fit is affected by multicollinearity. In such cases, only one of those two variables was used for development of the model.

RESULTS

Driver, Environment, and Road-Related Characteristics

Crash rates were higher for teen drivers than young-adult drivers, and rates for young-adult drivers were higher than for experienced drivers, as shown in Table 2.

Table 2: Crash Frequencies, Percentages, and Crash Rates by Driver Group: Driver, Environment and Road-Related Characteristics

Characteristic		Number of Crashes Involving Drivers						Crashes per 1000 Drivers			Crashes per Million VMT		
		Teen		Young adult		Experienced							
		Number	%	Number	%	Number	%	Teen	Young adult	Exp.	Teen	Young adult	Exp.
Total		49,165	100	44,802	100	184,079	100	100.3	82.9	45.3	17.8	8.7	3.5
Gender													
	Female	23,061	47	19,918	44	79,816	43	96.3	74.4	39.4	8.3	3.9	1.5
	Male	26,098	53	24,878	56	104,222	57	104.1	91.3	51.2	9.4	4.8	2.0
License Compliance													
	Valid licensed	46,137	94	40,565	91	173,343	94	94.1	75.1	42.7	16.7	7.8	3.3
	Not licensed	2,532	5	3,772	8	9,055	5	5.2	7.0	2.2	0.9	0.7	0.2
Restriction Compliance													
	No restrictions on driver's license	31,447	64	28,721	64	108,060	59	64.2	53.2	26.6	11.4	5.6	2.0
	Restricted license	14,874	30	13,118	29	67,997	37	30.4	24.3	16.7	5.4	2.5	1.3
Safety belt not used		2,993	6	2,641	6	6,261	3	6.1	4.9	1.5	1.1	0.5	0.1

Table 2: continued

Characteristic	Number of Crashes Involving Drivers						Crashes per 1000 Drivers			Crashes per Million VMT		
	Teen		Young adult		Experienced							
	Number	%	Number	%	Number	%	Teen	Young adult	Exp.	Teen	Young adult	Exp.
Total	49,165	100	44,802	100	184,079	100	100.3	82.9	45.3	17.8	8.7	3.5
Alcohol related	1,261	3	2,454	5	5,640	3	2.6	4.5	1.4	0.5	0.5	0.1
Light Conditions												
Daylight	33,862	69	29,250	65	129,084	70	69.1	54.1	31.8	12.3	5.7	2.4
Night or dark	15,195	31	15,449	34	54,634	30	31.0	28.6	13.5	5.5	3.0	1.0
Weather Conditions												
Good	41,262	84	36,601	82	152,284	83	84.2	67.8	37.5	14.9	7.1	2.9
Rain	4,780	10	4,522	10	16,873	9	9.8	8.4	4.2	1.7	0.9	0.3
Adverse conditions	2,937	6	3,527	8	14,371	8	6.0	6.5	3.5	1.1	0.7	0.3
Time of Crash												
5.00 - 9.00	6,242	13	5,653	13	32,260	18	12.7	10.5	7.9	2.3	1.1	0.6
9.00 - 13.00	6,986	14	7,592	17	34,857	19	14.3	14.1	8.6	2.5	1.5	0.7
13.00 - 17.00	15,586	32	12,058	27	51,123	28	31.8	22.3	12.6	5.6	2.3	1.0
17.00 - 21.00	12,067	25	10,791	24	44,091	24	24.6	20.0	10.9	4.4	2.1	0.8
21.00 - 5.00	8,263	17	8,684	19	21,661	12	16.9	16.1	5.3	3.0	1.7	0.4
Day of Week												
Weekdays	37,434	76	33,481	75	145,755	79	76.4	62.0	35.9	13.6	6.5	2.7
Weekend	11,727	24	11,311	25	38,295	21	23.9	20.9	9.4	4.2	2.2	0.7
Functional Class												
Rural roads	9,380	19	5,291	12	22,988	12	19.1	9.8	5.7	3.4	1.0	0.4
Urban interstate	113	0	163	0	799	0	0.2	0.3	0.2	0.0	0.0	0.0
Urban arterial	16,519	34	14,983	33	57,881	31	33.7	27.7	14.3	6.0	2.9	1.1
Urban collector	3,741	8	2,801	6	10,606	6	7.6	5.2	2.6	1.4	0.5	0.2
Urban local street	6,840	14	5,749	13	19,734	11	14.0	10.6	4.9	2.5	1.1	0.4
Crash Location												
On roadway	18,347	37	17,670	39	78,379	43	37.4	32.7	19.3	6.6	3.4	1.5
Intersection	26,619	54	23,500	52	95,470	52	54.3	43.5	23.5	9.6	4.5	1.8
Off roadway	4,188	9	3,615	8	10,194	6	8.5	6.7	2.5	1.5	0.7	0.2
Road Surface Conditions												
Dry	38,565	78	34,010	76	143,223	78	78.7	63.0	35.3	14.0	6.6	2.7
Wet	6,404	13	6,070	14	22,949	12	13.1	11.2	5.7	2.3	1.2	0.4
Debris	3,965	8	4,515	10	17,191	9	8.1	8.4	4.2	1.4	0.9	0.3
Work zones	1,061	2	1,294	3	2,355	1	2.2	2.4	0.6	1.2	0.8	0.0
Road Surface Character												
Straight and level	36,164	74	32,778	73	134,254	73	73.8	60.7	33.1	13.1	6.3	2.5
Straight not level	9,176	19	8,350	19	35,888	19	18.7	15.5	8.8	3.3	1.6	0.7
Curved	3,479	7	3,389	8	12,833	7	7.1	6.3	3.2	1.3	0.7	0.2

The teen-driver crash rate per 1,000 drivers was 100.3 while the young-adult driver crash rate was 82.9 and experienced-driver crash rate was 45.3. Teen-driver crash rate per million VMT was 17.80 while rates were 8.66 and 3.46 for young-adult and experienced drivers, respectively. Both teenage-driver and young-adult-driver involved crash rates per 1,000 licensed drivers were about twice that of experienced drivers. Teenage-driver crashes per million VMT were approximately five times that of experienced drivers, while young-driver crashes per million VMT were about two times that of experienced drivers. This indicated that teenage drivers have much more critical highway safety concerns on a per-mile-driven basis. Teen male-driver crash involvement (53%) was higher than that of teen female drivers (47%). Teen male drivers had higher crash rates than teen female drivers, as shown in Table 2. Teen female-driver involvement in crashes per 1,000 drivers was 96.3, while teen male-driver involvement in crashes per 1,000 drivers was 104.1. Female young-adult-driver crash rate per 1,000 teen female licensed drivers was about two times that of experienced drivers. The trend was similar for male drivers. Both teen-male and female-driver crashes per million VMT by licensed drivers were approximately five times that of experienced drivers, while young-adult driver crashes per million VMT by licensed drivers were about two to three times that of experienced drivers.

A majority of drivers involved in crashes had valid driver's licenses. More than 6% of teen drivers were not wearing seat belts, while 3% of teen drivers were under the influence of alcohol at the time of the crash. Teen drivers had a slightly higher crash involvement (54%) at intersections than experienced drivers (52%). On weekends and in dark lighting conditions, teen-driver crash involvement was slightly higher than that of experienced drivers. Teen-driver crash rates per 1,000 licensed teen drivers, when they were traveling on rural local roads or in the nighttime, were two to three times that of experienced drivers. In other cases, crash-involvement percentages were similar among teen and young-adult drivers as well as experienced drivers.

Vehicle and Crash-Related Characteristics

Teen drivers had higher crash involvement (68%) than that of experienced drivers (46%), as shown in Table 3. Almost 29% of teens were involved in crashes when they were driving vehicles made in 1994 or earlier, while only 16% of experienced drivers were involved in crashes driving those vehicles. This may be due to teens driving older vehicles more often.

A higher percentage of vehicles were destroyed due to crashes involving teen drivers (8%) compared with experienced drivers (5%). Teen drivers also had a higher crash-involvement percentage in collisions with a fixed object (15%) than experienced drivers (10%). However, teen-driver, crash-involvement percentages for many other vehicle and crash-related characteristics were similar to young-adult drivers as well as experienced drivers. Crash rates of vehicle and crash-related characteristics had a similar pattern as driver, environment, and vehicle-related crash rates when comparing teen, young-adult, and experienced drivers.

Table 3: Crash Frequencies, Percentages, and Crash Rates by Driver Group: Vehicle- and Crash-Related Characteristics

Characteristic		Number of Crashes Involving Drivers						Crashes per 1000 Drivers			Crashes per Million VMT		
		Teen		Young adult		Experienced							
		Number	%	Number	%	Number	%	Teen	Young adult	Exp.	Teen	Young adult	Exp.
Vehicle Damage													
	No damage	949	2	1,016	2	6,161	3	1.9	1.9	1.5	0.3	0.2	0.1
	Minor damage	11,262	23	10,465	23	52,083	28	23.0	19.4	12.8	4.1	2.0	1.0
	Functional	16836	34	16,007	36	67,953	37	34.4	29.6	16.7	6.1	3.1	1.3
	Disabling	16,012	33	14,110	31	48,165	26	32.7	26.1	11.9	5.8	2.7	0.9
	Destroyed	3,826	8	2,962	7	8,625	5	7.8	5.5	2.1	1.4	0.6	0.2
Vehicle Body Type													
	Automobile	33,432	68	29,195	65	83,981	46	68.2	54.0	20.7	12.1	5.6	1.6
	Van	1,410	3	1,469	3	17,867	10	2.9	2.7	4.4	0.5	0.3	0.3
	Pickup truck	8,075	16	7,342	16	38,396	21	16.5	13.6	9.5	2.9	1.4	0.7
	Sport utility vehicle	6,062	12	5,930	13	32,730	18	12.4	11.0	8.1	2.2	1.1	0.6
	Other	176	0	861	2	11,051	6	0.4	1.6	2.7	0.1	0.2	0.2
Vehicle Year													
	<1990	4,184	9	2,551	6	9,954	5	8.5	4.7	2.5	1.5	0.5	0.2
	1990 - 1994	9,805	20	6,285	14	20,589	11	20.0	11.6	5.1	3.5	1.2	0.4
	1995 - 1999	18,251	37	14,579	33	48,875	27	37.2	27.0	12.0	6.6	2.8	0.9
	2000 - 2004	13,109	27	15,203	34	66,857	36	26.8	28.1	16.5	4.7	2.9	1.3
	>2005	3,497	7	5,912	13	36,316	20	7.1	10.9	8.9	1.3	1.1	0.7
Vehicle Maneuver													
	Straight-following road	29,820	61	27,417	61	109,217	59	60.9	50.8	26.9	10.8	5.3	2.1
	Turn or changing lanes	9,474	19	7,400	17	26,650	14	19.3	13.7	6.6	3.4	1.4	0.5
	Avoiding maneuver	1,724	4	1,591	4	5,287	3	3.5	2.9	1.3	0.6	0.3	0.1
	Stopped, parking, or backing	7,499	15	7,769	17	40,935	22	15.3	14.4	10.1	2.7	1.5	0.8
	Other	431	1	413	1	1,352	1	0.9	0.8	0.3	0.2	0.1	0.0
Accident Class													
	Other non-collision and overturned	2,055	4	1,622	4	5,023	3	4.2	3.0	1.2	0.7	0.3	0.1
	Collision with vehicle	37,231	76	33,269	74	137,315	75	76.0	61.6	33.8	13.5	6.4	2.6
	Collision with pedestrian or animal	2,325	5	3,268	7	23,161	13	4.7	6.0	5.7	0.8	0.6	0.4
	Collision with object	7,544	15	6,631	15	18,542	10	15.4	12.3	4.6	2.7	1.3	0.3
Injury Severity													
	Fatal injury	83	0	117	0	436	0	0.2	0.2	0.1	0.0	0.0	0.0
	Disabled injury	486	1	431	1	1,786	1	1.0	0.8	0.4	0.2	0.1	0.0
	Injury	3,522	7	3,033	7	10,190	6	7.2	5.6	2.5	1.3	0.6	0.2
	Possible injury	3,436	7	3,186	7	12,843	7	7.0	5.9	3.2	1.2	0.6	0.2
	Not injured	39,390	80	36,127	81	150,954	82	80.4	66.9	37.2	14.3	7.0	2.8

Table 3: continued

Characteristic		Number of Crashes Involving Drivers						Crashes per 1000 Drivers			Crashes per Million VMT		
		Teen		Young adult		Experienced							
		Number	%	Number	%	Number	%	Teen	Young adult	Exp.	Teen	Young adult	Exp.
Ejection													
	Ejected	278	1	234	1	613	0	0.6	0.4	0.2	0.1	0.0	0.0
	Not ejected	46,216	94	42,342	95	173,972	95	94.3	78.4	42.8	16.7	8.2	3.3
	Trapped	287	1	239	1	1,144	1	0.6	0.4	0.3	0.1	0.0	0.0

For example, teen crash rates per 1,000 drivers were higher than that of experienced drivers in most of vehicle- and crash-related characteristics as observed in driver, environmental and vehicle-related crash rates. However, teen-driver crash rates per 1,000 drivers when operating an automobile, or making a turn, were about three times that of experienced drivers. Also, teen-driver crash rates per 1,000 drivers when the vehicle was destroyed, non-colliding/overturning, or colliding with other vehicles were much higher than that of experienced drivers. Teen-driver crash rates per million VMT in operating automobile, or turning, non-colliding and overturning, avoiding maneuver, or colliding with a fixed object were about six to nine times that of experienced drivers.

Contributory Causes

Contributory causes for young-driver crashes were also investigated using Kansas crash data. Many factors might have combined to produce circumstances that led to a traffic crash; there was rarely a single cause of such an event. Mainly these contributory causes could be divided into four categories: driver, roadway, environment, and vehicle-related factors. Driver-related contributory causes involve actions taken by or the condition of the driver of the motor vehicle. Contributory causes for teen, young-adult, and experienced drivers are provided in Table 4. Failure to give time and attention was the top-ranked driver contributory cause in teen-driver crashes, followed by speeding, failure to yield right of way, and disregarding traffic signs/signals. Those driver-related contributory causes were also the most critical factors among young-adult drivers and experienced drivers.

Crash rates for teen driver-related contributory causes per 1,000 licensed drivers were much higher than that of experienced drivers. Corresponding young-adult-driver-contributed crash rates were also higher than that of experienced drivers. Teen-driver-involved crashes per million VMT due to failure to give enough time and attention, failure to yield right of way, and speeding exceeded eight to nine times that of experienced drivers and twice that of young-adult drivers. The most frequent environment-related contributory causes for teen-driver-involved crashes were identified as animals in the road, followed by raining and snowing. The most common vehicle-related contributory causes for teen-driver crashes were identified as failure of brakes, followed by failure of tires.

Icy or slushy conditions and wet road surfaces were the most frequent road-related contributory causes for all age groups. Teen drivers' crash percentage due to animals in the road was less than that of young-adult drivers and experienced drivers. Conversely, the crash percentage of teen drivers due to rain was higher than that of young-adult drivers and experienced drivers. Teen drivers' crash percentage due to failure of brakes was higher than that of young-adult drivers and experienced drivers. Also, the crash percentage for teen drivers involved in crashes due to wet road surfaces was higher than that of young-adult drivers and experienced drivers.

Table 4: Crash Frequencies, Percentages, and Crash Rates for Contributory Causes

Characteristic	Number of Crashes Involving Drivers						Crashes per 1000 Drivers			Crashes per Million VMT		
	Teen		Young adult		Experienced							
	Number	%	Number	%	Number	%	Teen	Young adult	Exp.	Teen	Young adult	Exp.
Driver Related												
Failure to give time and attention	13,842	36	10,339	34	31,606	35	28.2	19.1	7.8	5.01	2.00	0.59
Speeding	5,699	15	4,608	15	11,518	13	11.6	8.5	2.8	2.06	0.89	0.22
Failure to yield right of way	5,193	14	3,649	12	11,575	13	10.6	6.8	2.9	1.88	0.71	0.22
Disregarding traffic sign/signal	4,942	13	4,108	13	12,231	13	10.1	7.6	3.0	1.79	0.79	0.23
Improper action	2,320	6	1,838	6	7,410	8	4.7	3.4	1.8	0.84	0.36	0.14
Turning or lane changing	1,361	4	1,040	3	3,577	4	2.8	1.9	0.9	0.49	0.20	0.07
Aggressive driving	1,335	3	1,122	4	2,000	2	2.7	2.1	0.5	0.48	0.22	0.04
Other driver factors	1,254	3	994	3	3,833	4	2.6	1.8	0.9	0.45	0.19	0.07
Alcohol impaired	1,190	3	2,208	7	5,345	6	2.4	4.1	1.3	0.43	0.43	0.10
Distraction	1,155	3	730	2	1,786	2	2.4	1.4	0.4	0.42	0.14	0.03
Environment Related												
Animal on road	1,742	50	2,290	54	15,226	68	3.6	4.2	3.8	0.63	0.44	0.29
Rain	681	20	716	17	2,372	11	1.4	1.3	0.6	0.25	0.14	0.04
Falling snow	257	7	420	10	1,514	7	0.5	0.8	0.4	0.09	0.08	0.03
Vision obstruction glare	249	7	143	3	607	3	0.5	0.3	0.1	0.09	0.03	0.01
Vehicle Related												
Brakes	218	34	133	25	369	20	0.4	0.2	0.1	0.08	0.03	0.01
Tires	157	25	151	29	486	26	0.3	0.3	0.1	0.06	0.03	0.01
Road Related												
Icy or slushy	998	44	1,222	50	4,076	50	2.0	2.3	1.0	0.36	0.24	0.08
Wet	757	34	640	26	1,967	24	1.5	1.2	0.5	0.27	0.12	0.04
Snow packed	208	9	304	13	1,053	13	0.4	0.6	0.3	0.08	0.06	0.02

Odds Ratios

To measure the association between teen drivers' and experienced drivers' contributory causes for crashes, Odds-Ratios (ORs) and 95% Confidence Intervals (CIs) were calculated using binary logit analysis (Long 1997). The OR is a widely used statistic in traffic safety studies for comparing whether the probability of a certain event is the same for two groups. The "odds" of an event (y) is defined as the probability of the outcome event occurring ($y = 1/x_1, x_2, ..., x_p$) divided by the probability of the event not occurring (Long 1997).

$$(4)\quad Odds = \frac{P\left(y = 1/x_1, x_2, ..., x_p\right)}{P\left(y = 0/x_1, x_2, ..., x_p\right)}$$

The ratio of odds of one variable ($odds_1$) and odds of other variable ($odds_0$),

$$(5)\quad odds\ ratio = \frac{odds_1}{odds_0}$$

is called Odds Ratio (OR). It gives the relative amount by which the odds a variable ($odds_1$) increases (OR > 1.0) or decreases (OR < 1.0) when the value of one of the predictor variables ($odds_0$) is increased by 1.0 unit. In this study, OR is used to access the injury risk of a particular age group, if a certain factor is present. Results of ORs and CIs of driver-contributory causes were examined among the three driver age groups. Comparisons were made between teen versus experienced groups, between teen versus young-adult groups, and between experienced versus young drivers, whose ages range between 15 and 24, as shown in Table 5.

Table 5: Odds Ratios (ORs) and Confidence Intervals (CIs) for Driver Contributory Factors

Contributory Causes	Teen versus Experienced			Teen versus Young Adult			Young versus Experienced		
	OR's	95% CI		OR's	95% CI		OR's	95% CI	
		Lower	Upper		Lower	Upper		Lower	Upper
Failed to give time and attention or fell asleep	1.08	1.04	1.11	1.11	1.08	1.15	1.01	0.98	1.04
Failed to yield right of way	1.06	1.04	1.09	1.16	1.11	1.21	1.01	0.99	1.04
Too fast for conditions	1.12	1.08	1.16	0.97	0.92	1.01	1.13	1.10	1.17
Followed too closely	1.06	1.02	1.11	1.01	0.96	1.06	1.06	1.02	1.09
Distraction	1.80	1.59	2.03	1.20	1.03	1.38	1.67	1.50	1.85
Disregard traffic signs, signal, or improper or no signal	0.81	0.77	0.86	0.88	0.82	0.95	0.86	0.82	0.90
Improper lane change, backing or passing	0.64	0.60	0.67	0.93	0.87	1.00	0.66	0.63	0.69
Restless/careless/aggressive/ antagonistic driving	1.61	1.50	1.72	0.95	0.88	1.03	1.64	1.55	1.75
Under influence of alcohol or drugs	0.51	0.48	0.55	0.41	0.38	0.44	0.83	0.79	0.87
Avoidance or evasive action	0.93	0.87	0.99	1.06	0.97	1.16	0.90	0.85	0.96
Made improper turn	0.95	0.88	1.02	1.16	1.06	1.28	0.89	0.84	0.95
Exceeded posted speed limit	2.03	1.85	2.23	1.14	1.02	1.27	1.92	1.77	2.09
Wrong side or wrong way, impeding traffic, too slow, improper parking	0.72	0.64	0.80	0.81	0.70	0.93	0.79	0.72	0.87
Ill medical condition	0.23	0.18	0.29	0.60	0.45	0.80	0.30	0.26	0.35

When interpreting results, ORs greater than one showed greater contribution from the particular factor for a considered driver-age group than the other driver-age group. For example, in teen versus experienced driver comparison, an OR value of 1.08 for failed to give and time and attention or fell asleep means teen drivers were 1.08 times more likely to be involved in crashes as experienced drivers due to failure to give enough time and attention or falling asleep. Similarly, teen drivers were more likely to be involved in crashes due to failure to yield right of way; driving too fast for conditions; following too closely; distractive, restless, careless, and aggressive driving; and exceeding posted speed limit compared with experienced drivers. Also, teen drivers were significantly more likely to have crashes due to failure to give time and attention or falling asleep, failure to yield right of way, distractive driving, making improper turns, or exceeding the posted speed limit when compared with

20- to 24-year-old drivers. The findings for young versus experienced drivers are identical to those of teen versus experienced drivers.

Multinomial Logit Model

A multinomial logit model was developed to investigate the injury severity of crashes involving young drivers, age 15 to 24. The dataset included 93,964 crashes from 2004 to 2008. The dependent variable had four categories: fatally/severely injured, injured, possible injured, or not injured. All the characteristics in Tables 2 and 3 were considered in developing the model. Most of these independent variables were treated as categorical variables. Thus, the numbers in Table 2 and 3 are summary statistics for variables in the estimations. Results of the young-driver injury-severity model are presented in Table 6. The model diagnostics showed a Likelihood Ratio Chi Square statistic of 35,102 whose p-value is < 0.001. In addition to the overall p-value, the logit model also reports the individual p-value for each independent variable. A low p-value means this particular independent variable significantly improves the fit of the multinomial logit model, showing that the variable has a significant impact on the model. Those significant variables are directly associated with injury severity of young-driver crashes. Some of significant variables had limited observations, but the results were not affected when those variables were removed or combined. The estimated model intercepts represent the mean impact of all variables that influence each injury severity level that were not included in the model. Negative coefficient estimates of the developed model show the reduced probability of potential injury severity, while positive coefficient estimates show the increased probability of potential injury severity. The significant variables in the model were age, gender, seatbelt use, air bag deployed, alcohol involvement, light condition, good weather, crash type, vehicle damage, vehicle maneuver, driver ejection, vehicle manufacturing year, and posted speed limit. The effects of each of these variables are explained in the following paragraphs.

According to the coefficients of the estimated logit model, teen drivers showed higher injury severity when involved in crashes. This could be expected because young drivers' inexperience may limit them to make necessary judgments and it may increase the severity when they are involved in crashes. The negative coefficient of the variable gender indicates that being a young male involved in a crash tends to decrease the probability of having a more severe injury. Seat belt-restrained young drivers were less likely to suffer severe injuries when involved in crashes. The effectiveness of seat belt restraint in reducing crash injuries is well known. The positive coefficient of the airbag deployed variable indicates that young drivers were more likely to suffer severe injuries when they were involved in crashes. This is not an expected result because generally air bags are used to reduce the injury severities when involved in crashes. Alcohol involvement was a significant factor that increased young-driver injury severity. Alcohol increases the probability of severe injuries among young drivers.

Decreased injury severities could be expected when streets are lighted and increased injury severities could be expected when streets are dark. According to the developed model, young drivers were less likely to suffer severe crashes whether streets are lighted or dark. Young drivers were more likely to suffer severe injuries when they involved in crashes during good weather. This may be because they may drive without proper precautions during good weather conditions. The estimated coefficient for off roadway crashes had a positive sign as expected. This means that young drivers' injury severity was higher when they were involved in run-off-the-road crashes. Collisions with fixed objects, other vehicles, pedestrians/animals increased young-driver injury severity. Also, involvement of non-collision and overturn crashes showed a higher injury severity for young drivers. Vehicle damage was a significant factor that increased young-driver injury severity, whether it was minor damage, functional, disabling, or destroyed at the time of crash. Young drivers were more likely to suffer severe injuries in crashes occurring when they were attempting a lane change or backing up. Conditions of ejection at the time of crash increased injury severity while non-ejection

Table 6: Driver Injury-Severity Model Results

Label	Parameters	Coef.	Std. Err.	p-value
intercept	Fatal and severe injury	-3.345	0.235	<0.001
	Injury	0.941	0.015	<0.001
	Possible injury	0.384	0.058	<0.001
	Not injured	-	-	-
AGE	Age 15-19	0.115	0.028	<0.001
	Age 20-24	0.000	-	-
GENDER	Driver male	-0.579	0.028	<0.001
	Driver female	0.000	-	-
VALID	Valid license	-0.076	0.050	0.130
	Not licensed	0.000	-	-
RESTRC	Restricted driver license	0.018	0.029	0.542
	Not restricted driver license	0.000	-	-
SEATB	Seat belt used	-0.546	0.057	<0.001
	Airbag deployed	0.875	0.043	<0.001
	Constraint system not used	0.000	-	-
ALCO	Alcohol involved	0.414	0.060	<0.001
	No alcohol	0.000	-	-
LIGHT	Dark	-0.132	0.053	0.012
	Streetlight on	-0.121	0.056	0.032
	Daylight	0.000	-	-
WEATHER	Sunny	0.257	0.066	<0.001
	Rain	0.047	0.047	0.3148
	Adverse weather conditions	0.000	-	-
WEEK	Weekday	0.033	0.032	0.297
	Weekends	0.000	-	-
RURAL	Rural roads	0.043	0.045	0.332
	Urban roads	0.000	-	-

Label	Parameters	Coef.	Std. Err.	p-value
LOCATION	Off roadway	0.096	0.051	0.016
	Intersection on roadway	-0.086	0.056	0.125
	Non-intersection on roadway	0.000	-	-
TYPE	Overturned	1.526	0.201	<0.001
	Collision with vehicle	0.282	0.063	<0.001
	Collision with pedestrian or animal	1.797	0.142	<0.001
	Collision with object	0.539	0.070	<0.001
	Other non-collision and others	0.000	-	-
DAMAGE	Destroyed	3.033	0.175	<0.001
	Disabling	2.956	1.629	<0.001
	Functional	2.552	0.052	<0.001
	Minor damage	1.092	0.041	<0.001
	No damage	0.000	-	-
PANUM	Driver alone	0.052	0.029	0.211
	With passengers	0.000	-	-
AUTO	Automobile	0.139	0.139	0.073
	Other vehicle	0.000	-	-
MANU	Back up	0.468	0.168	<0.001
	Turn or changing lanes	0.612	0.612	<0.001
	Straight-following	0.000	-	-
EJECT	Not Ejected	-0.517	0.183	0.005
	Ejected	2.582	0.140	<0.001
	Trapped	0.000	-	-
NEW	Vehicle manufacturing year > 2000	-0.177	0.030	<0.001
	Vehicle manufacturing year <=2000	0.000	-	-
WZONE	Work zone	-0.197	0.125	0.115
	Not a work zone	0.000	-	-
SPEED	Posted speed limit	0.016	0.002	<0.001

Goodness-of-Fit Tests

Pearson Chi-Square	86,108	<0.001
L.R. Chi Square	35,102	<0.001

decreased injury severity of young drivers. Youth driving in newer vehicles were less likely to suffer severe injuries as expected. Driving on higher-posted speed limit roadways was also a significant factor that increased young drivers' injury severity.

The identified relationships for variables age, gender, seat belt use, airbag deployed, alcohol involvement, ejection, and speed were also identified in previous other young-driver-related research (Dissanayake and Lu 2002, Vachal and Malchose 2009). Variables such as valid licenses, restrictions on driver's licenses, rainy weather conditions, driving through intersections on roadways, driving alone, and driving through work zones were not significant at 95% confidence interval.

DISCUSSION AND COUNTERMEASURE IDEAS

Engineering-Related Countermeasure Ideas

Young drivers' crash rates are higher than that of experienced drivers', and therefore protective devices, crashworthy cars, and safer road infrastructures will particularly reduce young drivers' risk. While driving, a young driver's behavior is influenced by his or her general frame of mind, which among other things, reflects the situation just behind or approaching. As shown in the logit model results developed in this study, high speeds was one of the risk factors, as young drivers lack experience. Hence, predictable traffic situations and low complexity resulting from an improved road infrastructure are beneficial for young drivers. In particular, rural road and off-roadway crash involvement and high-injury risk could be reduced by safer road infrastructures such as rumble strips and lane departure warnings. Also, road infrastructures should be improved to avoid hitting animals. This is a main road-related contributory factor for crashes in Kansas.

Policy-Related Countermeasure Ideas

In particular, the Graduated Licensing System is designed to address teen and inexperienced young drivers' crash risk by letting them acquire driving experience under low-risk conditions (Williams, Ferguson, and Wells 2003). The goal of the licensing process, including training, should be to create drivers who are safe, increasing awareness of their own limitations and of the risks inherent to drivers.

Education-Related Countermeasure Ideas

Failure to give time and attention, failure to yield right of way, driving too fast for conditions, and following too closely were the main contributory causes that could be included in education programs in order to increase awareness. These are also effective countermeasures for decreasing young-driver risk. A driver's safety-related characteristics are formed well before the age at which he or she legally begins driving; hence, education programs and communication programs in schools can be focused on children at much younger ages than the legal driving age (OECD 2006). Training programs could be focused more on backing up, turning, and changing lanes because young drivers show high injury severity for those maneuvers when they are involved in crashes. Another factor is preventing teen drivers from adopting bad habits and informal rules in traffic such as speeding, drinking while driving, etc. (OECD 2006). According to the model developed, teen drivers are at high risk for injuries. Also, crash rates show teen drivers' involvement in crashes are higher than young-adult drivers. Hence, parental management practices may be important influences on teen-driver practices and safety.

Enforcement-Related Countermeasure Ideas

Enforcement will have a proportionately higher impact on young drivers, as they more frequently violate traffic rules such as driving without a valid driving license and not obeying driver's license restrictions (Hanna et al. 2006). The results show that 5% of young drivers were not licensed and 37% of young drivers have restrictions on their licenses. Special attention should be paid to unlicensed driving because the more regulated and demanding the driving process becomes, the more tempted teens will be to drop out of the licensing process and drive without a license. However, it is difficult for police to specifically identify young drivers on the road, making the young-driver-specific countermeasures difficult to enforce.

According to the developed model, one of the significant variables for reducing injury risk is increasing seat belt usage. In 2010, Kansas turned to a primary seat belt-restraint law from a secondary law for teen drivers 15 to 17 years old. A primary seat belt law allows a law enforcement officer to stop a vehicle and issue a citation for not wearing a seat belt. A secondary seat belt-restraint law only allows for a citation to be issued if the vehicle is stopped for another primary violation. Also, avoiding alcohol-involved driving is an important factor in reducing injury risk. It is also a factor in reducing crash involvement. Age 21 is the legal drinking age in Kansas, so young drivers are restricted from alcohol use, but alcohol-involved crashes are a significant factor for increased crash injuries. Hence, enforcement is needed especially in locations where high alcohol use is expected. Distraction is a main contributory cause of teen-driver crashes. Many drivers use audio entertainment systems and mobile phones, but very few use on-vehicle visual displays such as a DVD (OECD 2006). Implementation of laws, such as prohibiting mobile phone use while driving and banning visual displays would be beneficial, particularly for young drivers.

Measures focusing on improving the safety of all road users under all conditions will also be beneficial for young drivers, who frequently exhibit dangerous behaviors. Not all effective countermeasures can be implemented simultaneously. However, some countermeasures are less effective when introduced in isolation (OECD 2006).

SUMMARY AND CONCLUSIONS

This study explored the detailed characteristics of young-driver-involved crashes and contributory factors in Kansas, and compared those with experienced drivers. Crash data were obtained from KDOT, driver's license data were obtained from the US Department of Transportation, and annual vehicle miles driven were obtained from the National Household Travel Survey 2010. Young drivers were further divided into two groups: teen and young adults. A detailed frequency analysis and crash-rate analysis were carried out for both groups. Furthermore, a detailed frequency analysis was carried out for experienced drivers and comparisons were made among each driver group. The number of teen-driver-involved crashes per 1,000 licensed teen drivers was higher than that of young and experienced drivers. Teen drivers in Kansas were at considerable risk of motor vehicle crashes compared with experienced drivers. Factors that increase young drivers' injury severity, such as alcohol involvement and high speed, can be used for teen crash-prevention efforts. Many complex factors influence and contribute to teen-driving behavior. Increased crash frequency and risk for this age group has been attributed to failure to give time and attention, falling asleep, failure to yield right of way, driving too fast for conditions, following too closely, or distraction compared with experienced drivers.

Based on identified critical factors, countermeasure ideas were suggested to improve the safety of young drivers. Understanding these contributory factors could lead to better crash mitigation strategies. It is important for teen drivers to gain better education about these critical factors that are helpful to increase training, prevent crashes, and minimize driving risk.

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An Analysis of a Strategic Transformation Plan: The Case of Alaska Airlines

by Paul Caster and Carl Scheraga

In 2003, amid the turmoil of the U.S. airline industry in the post-9/11 environment, the senior management of the Alaska Air Group announced a "strategic vision" entitled "Alaska 2010." The pronouncement articulated positions with regard to cost leadership, product differentiation, and growth. This study empirically assesses the efficacy of this decision with regard to the major network carrier of the air group, Alaska Airlines. The analysis focuses on the period beginning with the announcement and ending in 2010.

The implementation of such a strategic protocol is dynamic and inter-temporal in nature. Therefore, it is often difficult to assess the effectiveness of changes in strategies, particularly since such effectiveness is often a function of the confounding forces of organizational strategy and market conditions. Thus, this study utilizes the multi-period methodology of the strategic variance analysis of operating income.

This methodology decomposes operating income into three components: (1) growth, (2) price recovery, and (3) productivity. This is of particular interest from a strategic planning perspective, as the price component evaluates a company's product differentiation strategy while the productivity component evaluates whether an airline's low cost strategy was successful because of efficiency gains.

INTRODUCTION

In 2003, the U.S. airline industry was in turmoil. Airline traffic continued to be below 2001 levels, still reeling from the aftermath of the 9/11 terrorist attacks. A slow U.S. economy combined with rising fuel costs produced billions of dollars in losses for airlines. In addition, both US Airways and United Airlines filed for bankruptcy protection in 2002. In such a challenging business environment, it was clear that airlines had to change their operating strategies.

The management of Alaska Air Group, led by Chairman, President, and CEO William S. Ayer, did just that, announcing a "strategic vision" called "Alaska 2010." The plan was communicated to employees in June 2003, and elements of the plan were made public in the company's annual report to shareholders for the year ended December 31, 2003, as well as in subsequent years. Highlights of the plan included a goal of making permanent cost reductions to save the company $307 million per year, and to drive down the non-fuel unit cost to 7.25 cents per available seat mile (Ayer 2004). In the letter to shareholders, Ayer stated, "Our task is to make the critical changes necessary to transform ourselves into a thriving enterprise."

Alaska Air Group consists of two airlines: Alaska Airlines and Horizon Air Industries. As explained in the annual report to shareholders, the "business plans, competition, and economic risks differ substantially" (SEC 2004). The focus of this research is on the impact of the Alaska 2010 strategic plan on Alaska Airlines, since it is the major network carrier in the group.

From a research perspective, questions arose as to how Alaska Airlines was performing relative to other airlines. It was also asked if management was correct in perceiving a need to transform the company's operations. After all, by its own perception, the company was doing very well relative to the industry. In 2001, the company reported that "Alaska [Airlines] posted remarkable results following the 9/11 tragedy. For instance, industry traffic was down 19% in the fourth quarter, and

Alaska's was only down 5.6%. Likewise, yield per revenue passenger mile and unit revenues were down 17% and 20% respectively for the major carriers combined, while Alaska's were down only 7.3% and 5.5%." (Kelly 2002). Similarly, in 2002, the company stated that "Alaska [Airlines] had the best traffic, revenue, and yield performance of the majors." (Kelly 2003). Nonetheless, the company was losing money.

This paper assesses the Alaska 2010 strategic transformation using strategic variance analysis (SVA). SVA is used to analyze a company's profitability by breaking it down into strategic components, namely, cost leadership, product differentiation, and growth (Horngren et al. 2000, 2006, 2012). Sopariwala (2003) extended the analysis to include a fourth component, capacity underutilization. SVA has been used by Mudde and Sopariwala (2008) and Bailey et al. (2009) to analyze a given airline's profitability, and by Caster and Scheraga (2011) to analyze the performance of all U.S. network carriers.

THE ALASKA AIR GROUP LONG-TERM STRATEGIC PLAN

In discussing "Alaska 2010," the Alaska Air Group long-term strategic plan, Ayer noted that the company's goal for the future was "a combination of ideas that generate savings or increase revenue while enhancing our standing with customers" (Ayer 2004). Ayer stated that cost management was a significant challenge. He went on to explain why the plan was called "Alaska 2010." He said that "if we make the right moves now, 2010 will be the year we look back with great pride at how we transformed ourselves - - how we took control and willed ourselves to be one of the preeminent airlines in the United States" (Ayer 2004).

Additional details of the strategic plan emerged in the annual report to shareholders for calendar year 2004. In the letter to shareholders dated April 11, 2005, Ayer (2005) explained that permanent reductions in annual costs of $185 million had been achieved. This reduction was accomplished in part through a fuel hedging program, in addition to savings achieved through a "top-to-bottom review of our supply chain." Cost savings were also achieved by streamlining the fare structure, by improving the website for the purchase of fares online, and by improving turn times of aircraft between flights. Ayer acknowledged that competitors were improving their cost structures at an even faster pace than Alaska Air Group, and to that end, it was necessary to reduce the workforce, in part by outsourcing some of its maintenance operations. Ayer (2005) also reported that "a big part of our Alaska 2010 plan focuses on achieving competitive labor costs for all major work groups." The company estimated that wages and benefits were approximately $125 million above market, with most of that amount due to pilots.

Although some details of the strategic plan are disclosed in the annual reports, the information does not provide a complete picture. In fact, only those details that management chooses to disclose are available. Strategic variance analysis provides a better means for analysis of Alaska's performance. It provides an independent lens through which to view and analyze that performance. In addition, it allows for benchmarking with peer companies, in this case, the other network carriers. The following two sections provide a description of strategic variance analysis and the details on calculation and interpretation of the variances.

STRATEGIC VARIANCE ANALYSIS

SVA was introduced by Shank and Govindarajan (1993) as a management tool that combined the then rising field of business strategy to traditional profit variance analysis in cost accounting. SVA, as modified by Sopariwala (2003), takes a company's profit (or loss) and breaks it down into four components: growth, price-recovery, productivity, and capacity underutilization. Each component is discussed in greater detail in the following section of the paper. Variances are defined as the differences between actual results and expected results, and they are calculated for each component.

Sopariwala (2003) based his version of SVA on Horngren et al. (2000). Horngren et al. (2012, 478-485) illustrate how SVA can be used to analyze profitability "from one period to *any* future period." Their illustration shows how to calculate and interpret the growth component, the price-recovery component, and the productivity component. As discussed in Horngren et al. (2012), the price-recovery component is related to product differentiation and the productivity component is related to cost leadership.

Product differentiation and cost leadership are two of the three generic strategies developed by Porter (1980, 35) for "outperforming competitors in the industry." His third strategy is "focus," which involves specializing in a niche area of the market. Cost leadership means that a company is recognized throughout the industry as the low cost provider of goods or services. Porter states that it requires "a great deal of managerial attention to cost control." (Porter 1980, 35). According to Porter (1980, 37), product differentiation involves "creating something that is perceived *industrywide* as being unique. Having a unique product or service leads to brand loyalty, which allows a company to charge a higher price, thereby outperforming others in the industry without having low costs as a primary objective. Horngren et al. (2012) refer to this as price-recovery, because the company is able to recover its higher costs through higher revenues, thus earning a decent return.

Porter's third strategy is similar to the other two, in that a company chooses to follow a low cost strategy or a product differentiation strategy, but it does so in a narrow niche of the market. Therefore, the focus strategy is not an industry-wide strategy.

Porter then goes on to describe companies that are "stuck in the middle." It is possible that Alaska Air Group perceived itself in 2003 as a company that could be "stuck in the middle." A company that is stuck in the middle "lacks the market share, capital investment, and resolve to play the low-cost game, the industry-wide differentiation necessary to obviate the need for a low-cost position, or the focus to create differentiation or a low-cost position in a more limited sphere" (Porter 1980, 41).

SVA is an ideal technique for assessing the success or failure of a long-term strategic plan, such as Alaska 2010. Management of Alaska Airlines measures its success by looking at profitability, goals for reducing its cost structure, and customer satisfaction. But the acid test is how Alaska Airlines has performed relative to its peers. SVA provides easy comparisons between Alaska Airlines and the rest of the U.S. network carriers.

DEVELOPMENT OF VARIANCES

The variances used for SVA are calculated based on Sopariwala (2003), using the four components of a company's performance as described in Mudde and Sopariwala (2008). Each component, and the variances associated with that component, is explained as follows:

Growth Component

The growth component measures the change in operating income due to a change in revenue passenger miles (RPMs). Four separate variances are calculated related to changes in RPMs. The revenue effect of growth captures the change in revenues due to a change in RPMs, holding air fares (revenue per RPM) constant. As explained in Mudde and Sopariwala (2008, 25), it would show "higher expected revenue due to higher RPMs."

The other three variances relate to costs and expenses, namely, fuel costs, flight-related costs, and passenger-related costs. Mudde and Sopariwala (2008) base the cost drivers on Banker and Johnston (2003), who suggested volume-based and non-volume-based cost drivers appropriate for the airline industry. The fuel cost effect of growth is calculated using available seat miles (ASMs) as the cost driver, while holding the price of fuel constant. The variance is calculated based on budgeted ASMs compared with actual ASMs. Thus, an airline would experience higher fuel costs and a corresponding decline in operating profit if it experienced growth in the market that exceeded expectations, while holding the price per gallon of jet fuel constant to isolate the impact of growth. In a similar manner, expectations and variances are developed for the growth effect of flight-related and passenger-related costs, while holding all else equal.

Price-Recovery Component

The price-recovery component measures the change in operating income due to changes in the prices of inputs and outputs, holding all else equal. Four separate variances are calculated related to changing prices. The revenue effect of price-recovery captures the change in airfares, holding RPMs constant. The other three variances relate to the cost of inputs, namely, fuel costs, flight-related costs other than fuel, and passenger-related costs. For example, if the cost of jet fuel increases in the current period, operating profit would decline, holding gallons of fuel used and budgeted ASMs constant.

Productivity Component

The productivity component measures the change in operating income due to changes in the use of inputs, holding all else equal. Productivity is measured in terms of fuel usage efficiencies and passenger cost related efficiencies, as calculated by Mudde and Sopariwala (2008). Three variances are calculated, two of which are related to fuel usage. The first fuel usage efficiency variance measures fuel usage per gallon, holding the cost per gallon and budgeted ASMs constant. Gallons used per ASM in the previous period are the expectation for the current period, and the variance is then based on actual gallons used per ASM in the current period. The passenger load factor also has an impact on fuel usage, so a second fuel usage variance is calculated by holding the price per gallon constant and the gallons used per ASM constant, while comparing budgeted ASMs to actual ASMs in the current period. The third variance is calculated based on the difference between budgeted revenue passengers and actual revenue passengers served, while holding the cost per passenger constant. The variance is favorable, and thus operating profit would increase if an airline achieves the same RPMs while carrying fewer passengers, and hence the cost associated with that would decrease.

Capacity Underutilization Component

The capacity underutilization component measures the change in operating income due to changes in capacity, holding all else equal. Three variances are calculated, each of which involves the impact on flight-related costs (excluding fuel costs). The first variance is the cost of acquiring additional capacity that goes unused in the current period. The variance is calculated by subtracting actual RPMs in the current period from actual ASMs in the current period. The second variance is the cost of underutilization of available capacity. The variance is simply the change in actual ASMs over the period under study, holding the cost per ASM constant. The third variance measures the impact of a change in capacity actually used. The variance is simply the change in RPMs over the period under study, holding the cost per ASM constant.

THE DATA SET

Data were obtained from two sources: The International Civil Aviation Organization, *Financial Data: Commercial Air Carriers, Series F* and *Traffic: Commercial Air Carriers, Series T*, and from the U.S. Department of Transportation, Bureau of Transportation Statistics, *Transtats Aviation Database*. We chose three, three-year time periods for the analysis, 2001 to 2003, 2004 to 2006, and 2007 to 2009. We also examine the one-year period from 2009 to 2010 to include the last year of Alaska's strategic plan. The three-year time frame is consistent with the work of Caster and Scheraga (2011).

Alaska Airlines is a U.S. network air carrier, as classified by the Department of Transportation, therefore, we collected data on the other network air carriers for benchmarking purposes. In the first two three-year time periods, we construct a composite based on the seven network carriers: Alaska, American, Continental, Delta, Northwest, United, and US Airways. In the last three-year time period, US Airways was dropped from the analysis due to its merger with America West, which would make the data non-comparable to the earlier periods.

RESULTS OF THE STRATEGIC VARIANCE ANALYSIS

Table 1 provides the financial data for Alaska Airlines. It is interesting to note, just from the raw data, that operating profit changed dramatically during the period. For the year ended December 31, 2000, Alaska Airlines reported a net operating loss of $12,375,000. The annual operating loss grew to $103,629,000 for the year ended December 31, 2006. But three years later, they reported an annual net operating profit of $208,421,000.

Table 1: Alaska Airlines – Financial Data ($)

	2000	2003	2006	2009
Operating revenues	1,759,867,000	2,027,376,000	2,692,507,000	3,005,999,000
Operating expenses	1,772,242,000	2,037,996,000	2,796,136,000	2,797,578,000
Flying operations	662,612,000	737,423,000	1,141,147,000	1,014,188,000
Maintenance	204,115,000	244,001,000	269,370,000	293,567,000
Depreciation and amortization	83,860,000	119,467,000	137,811,000	178,488,000
User charges	35,185,000	57,771,000	51,976,000	54,161,000
Station expenses	266,623,000	346,011,000	393,344,000	369,387,000
Aircraft and traffic servicing	301,808,000	403,782,000	445,320,000	423,548,000
Passenger services	155,622,000	200,381,000	207,062,000	211,298,000
Promotion and sales	248,499,000	218,672,000	209,078,000	176,864,000
General & Administrative	104,851,000	103,267,000	364,515,000	216,133,000
Transport related expenses	10,875,000	11,003,000	21,833,000	283,492,000
Operating profit	-12,375,000	-10,620,000	-103,629,000	208,421,000

Data Source: International Civil Aviation Organization, *Financial Data: Commercial Air Carriers, Series F*, Montreal, Quebec, Canada, 2000, 2003, 2006, and 2009

Table 2 provides the operating data and Table 3 provides the fuel data for Alaska Airlines needed to perform the strategic variance analysis. Table 4 reclassifies the operating data to show fuel costs, flight-related costs less fuel costs, and passenger-related costs, the three cost drivers used in prior studies (e.g., Caster and Scheraga 2011, Mudde and Sopariwala 2008). Table 5 uses the data from Tables 2, 3, and 4 to calculate the data needed for strategic variance analysis of Alaska Airlines.

Table 2: Alaska Airlines – Operational Data

	2000	2003	2006	2009
Revenue passengers	13,512,111	15,046,919	17,148,313	15,523,498
Revenue passenger miles	11,976,022,528	14,553,539,641	17,810,371,493	18,315,689,560
Available seat miles	17,291,684,686	20,803,557,288	23,257,684,435	23,070,335,242

Data Source: International Civil Aviation Organization, *Traffic: Commercial Air Carriers, Series T*, Montreal, Quebec, Canada, 2000, 2003, 2006, and 2009

Table 3: Alaska Airlines – Fuel Data

	2000	2003	2006	2009
Total gallons used	302,437,826	336,686,178	353,844,599	303,896,417
Total fuel costs	286,073,111	296,732,291	716,950,639	529,385,990
Average fuel cost per gallon ($)	0.95	0.88	2.03	1.74

Data Source: U. S. Department of Transportation, Research and Innovative Administration, Bureau of Transportation Statistics, *TranStats Database*, Washington, D.C., 2000, 2003, 2006, and 2009

Table 4: Alaska Airlines – Reclassified Financial Data ($)

	2000	2003	2006	2009
Total operating revenues	1,759,867,000	2,027,376,000	2,692,507,000	3,005,999,000
Less: Total operating expenses	1,772,242,000	2,037,996,000	2,796,136,000	2,797,578,000
Fuel costs	286,073,111	296,732,291	716,950,639	529,385,990
Flight-related costs	935,861,889	1,118,809,709	1,424,787,361	1,667,780,010
Passenger-related costs	550,307,000	622,454,000	654,398,000	600,412,000
Operating income/(loss)	-12,375,000	-10,620,000	-103,629,000	208,421,000

	2000	2003	2006	2009
Flying operations	662,612,000	737,423,000	1,141,147,000	1,014,188,000
Less: Fuel Cost	286,073,111	296,732,291	716,950,639	529,385,990
Flying operations (excluding fuel cost)	376,538,889	440,690,709	424,196,361	484,802,010
Maintenance	204,115,000	244,001,000	269,370,000	293,567,000
Passenger service	155,622,000	200,381,000	207,062,000	211,298,000
General and administrative	104,851,000	103,267,000	364,515,000	216,133,000
Depreciation and amortization	83,860,000	119,467,000	137,811,000	178,488,000
Transport related	10,875,000	11,003,000	21,833,000	283,492,000
Total flight-related costs	935,861,889	1,118,809,709	1,424,787,361	1,667,780,010

	2000	2003	2006	2009
Aircraft and traffic servicing	301,808,000	403,782,000	445,320,000	423,548,000
Promotion and sales	248,499,000	218,672,000	209,078,000	176,864,000
Total passenger-related costs	550,307,000	622,454,000	654,398,000	600,412,000

Data Sources: 1) Data Source: International Civil Aviation Organization, *Financial Data: Commercial Air Carriers, Series F*, Montreal, Quebec, Canada, 2003, 2006, and 2009 and 2) U. S. Department of Transportation, Research and Innovative Administration, Bureau of Transportation Statistics, *TranStats Database*, Washington, D. C., 2003, 2006, and 2009

Table 5: Alaska Airlines – Data Used in Strategic Variance Analysis[1]

	2000	2003	2006	2009
Total operating revenues ($)	1,759,867,000	2,027,376,000	2,692,507,000	3,005,999,000
Revenue passenger miles (RPMs)	11,986,220,472	14,553,539,641	17,822,404,781	18,361,670,904
Average revenue per RPM	0.147	0.139	0.151	0.164
Revenue passenger miles (RPMs)	11,986,220,472	14,553,539,641	17,822,404,781	18,361,670,904
Available seat miles (ASMs)	17,314,311,918	20,803,557,288	23,275,770,873	23,144,012,157
Passenger load factor (%)	69.23%	69.96%	76.57%	79.34%
Hence, budgeted available seat miles		21,022,850,818	25,476,236,573	23,980,043,662
Revenue passenger miles (RPMs)	11,986,220,472	14,553,539,641	17,822,404,781	18,361,670,904
Revenue passenger enplanements	13,524,685	15,046,919	17,164,501	15,561,087
Average revenue passenger miles per passenger ($)	886.25	967.21	1038.33	1179.97
Hence, budgeted revenue passenger enplanements		16,421,527	18,426,602	17,683,860
Number of gallons used	302,437,826	336,686,178	353,844,599	303,896,417
Available seat miles (ASMs)	17,314,311,918	20,803,557,288	23,275,770,873	23,144,012,157
Average number of gallons per ASM	0.0174675	0.0161841	0.0152023	0.0131307
Total flight-related costs ($)	935,861,889	1,118,809,709	1,424,787,361	1,667,780,010
Available seat miles (ASMs)	17,314,311,918	20,803,557,288	23,275,770,873	23,144,012,157
Average flight-related cost per ASM ($)	0.054	0.054	0.061	0.072
Total passenger-related costs ($)	550,307,000	622,454,000	654,398,000	600,412,000
Revenue passenger enplanements	13,524,685	15,046,919	17,164,501	15,561,087
Average cost per revenue passenger ($)	40.69	41.37	38.13	38.58
Revenue passenger (RPMs)	11,986,220,472	14,553,539,641	17,822,404,781	18,361,670,904
Available seat miles (ASMs)	17,314,311,918	20,803,557,288	23,275,770,873	23,144,012,157
Idle or unused capacity (ASMs)	5,328,091,446	6,250,017,647	5,453,366,092	4,782,341,252
Hence, budgeted idle capacity (ASMs)		6,469,311,177	7,653,831,792	5,618,372,758

Data Sources: 1) International Civil Aviation Organization, *Financial Data: Commercial Air Carriers, Series F*, Montreal, Quebec, Canada, 2000, 2003, 2006, and 2009, 2) International Civil Aviation Organization, *Traffic: Commercial Air Carriers, Series T*, Montreal, Quebec, Canada, 2000, 2003, 2006, and 2009, and 3) U. S. Department of Transportation, Research and Innovative Administration, Bureau of Transportation Statistics, *TranStats Database*, Washington, D. C., 2000, 2003, 2006, and 2009

[1]Budgeted Available Seat Miles from year x to year y = Revenue Passenger Miles (year y) / Passenger Load Factor (year x), Budgeted Revenue Passengers Enplanements from year x to year y = Revenue Passenger Miles (year y) / Average Revenue Passenger Miles per Passenger (year x), and Budgeted Idle Capacity in year y = Budgeted Available Seat Miles (year y) – Revenue Passenger Miles (year y). [See Mudde and Sopariwala (2008).]

Table 6a provides the strategic variance analysis for Alaska Airlines and six other network carriers for the three-year time frame ending December 31, 2003. The first column shows the results for Alaska Airlines, and the last column is a composite of all of network carriers in the sample. The annual net operating loss in 2003 was $10.6 million, an improvement of approximately $1.8 million compared with 2000 (Table 1). Strategic variance analysis provides a breakdown of the change in annual operating profitability. Alaska Airlines achieved productivity gains of nearly $84 million. More than half of the gain is from passenger-related costs, i.e., lower costs due to flying more miles per passenger. The growth component contributed approximately $59 million to increased profitability. All of that increase is due to the revenue effect of growth, meaning that Alaska Airlines had higher RPMs in 2003 than in 2000. In contrast, the price-recovery component showed a large decrease of approximately $93 million. Nearly all of that decrease is due to the revenue effects, meaning that Alaska Airlines charged lower airfares in 2003 than in 2000. The capacity underutilization component shows a decrease of more than $48 million. A large increase in ASMs led to a $190 million decrease in operating profits due to underutilization of available capacity. However, by increasing its RPMs in the period, Alaska enjoyed a $139.5 million increase in operating profits due to the capacity it actually used.

Table 6b provides the strategic variance analysis for Alaska Airlines and six other network carriers for the three-year time frame ending December 31, 2006. The net operating loss increased by approximately $93 million compared with December 31, 2003 (Table 1). The strategic variance analysis reveals results very similar to the prior period. Alaska Airlines' operating profits improved by almost $73 million due to the growth component, with all of that improvement attributable to the revenue effect of growth. Productivity gains were achieved from all three measures, amounting to an improvement of $166.2 million in annual operating profits. Capacity underutilization was not material in this period, although the pattern was similar to the prior period in terms of unused ASMs and RPMs actually flown. However, the decrease in profitability due to the price-recovery component of more than $334 million in the period overwhelmed the increases in the other three components. Although Alaska Airlines raised its fares in this time period, the revenue effect of fare increases was not sufficient to recover increased costs of fuel, primarily, and also other flight-related costs.

Table 6c provides the strategic variance analysis for Alaska Airlines and five other network carriers for the three-year time frame ending December 31, 2009. Alaska Airlines experienced dramatic improvement in its annual operating profits, going from a loss of $103.6 million to a profit of $208.4 million (Table 1). The first three components of the strategic variance analysis show positive impacts on annual operating profits. The growth component was much less of a factor than in the previous two periods, contributing just $6.5 million to increased profitability. Productivity gains were quite significant, contributing $186.2 million to increased profitability. Alaska Airlines was able to significantly reduce the amount of jet fuel used, resulting in a savings of approximately $85 million. It also had a savings of $81.7 million in passenger-related costs by flying more miles per passenger than in the earlier period. Perhaps most interesting is the $129.4 million increase in annual operating profits due to the price-recovery component. The revenue effect of price-recovery shows that Alaska Airlines was able to charge higher fares, which helped to recover higher flight-related costs. They also achieved some cost savings in fuel costs during the period. Capacity underutilization was relatively insignificant during the period, with a decrease in operating profitability of approximately $10 million. The fact that management was able to increase profitability through higher airfares and through further gains in productivity shows that a blended strategy, as discussed in Caster and Scheraga (2011) was in use during this three-year period.

Table 6a: Strategic Variance Analysis 2001-2003

	Alaska	American	Continental	Delta	Northwest	United	US Airways	Composite
GROWTH COMPONENT 2001-2003								
Revenue effect	378,764,093	542,547,377	-795,290,979	-2,647,808,299	-1,474,097,506	-3,507,658,420	-1,784,221,315	-9,232,678,935
Fuel cost effect	-61,569,552	-65,736,738	112,306,023	305,811,129	235,419,092	419,454,747	217,716,581	1,181,317,908
Flight-related cost effect	-139,500,579	-202,026,324	298,061,677	1,002,067,784	513,324,575	1,418,489,068	750,982,716	3,547,436,803
Passenger-related effect	-118,438,798	-160,584,629	231,453,819	722,530,896	478,923,290	992,810,816	508,832,697	2,688,384,420
TOTAL	**59,255,164**	**114,199,686**	**-153,469,460**	**-617,398,489**	**-246,430,549**	**-676,903,789**	**-306,689,321**	**-1,815,539,804**
PRICE-RECOVERY COMPONENT 2001-2003								
Revenue effect	-111,255,093	-1,256,347,377	-1,000,592,021	1,529,988,299	-298,727,494	-2,425,892,580	-635,371,685	-4,253,284,065
Fuel cost effect	23,727,216	-296,749,205	-8,277,005	-320,690,710	43,972,399	-320,743,696	62,554,603	-818,195,494
Flight-related cost effect	4,982,349	-1,564,386,963	3,961,889	-2,743,783,895	-471,616,518	-506,749,111	-291,009,423	-5,452,683,518
Passenger-related effect	-10,518,693	762,694,658	124,377,854	-309,539,166	-32,658,773	300,230,296	-8,588,462	636,226,823
TOTAL	**-93,064,220**	**-2,354,788,887**	**-880,529,282**	**-1,844,025,473**	**-759,030,386**	**-2,953,155,090**	**-872,414,966**	**-9,887,936,254**
PRODUCTIVITY COMPONENT 2001-2003								
Fuel cost effect	24,192,121	140,261,783	112,548,760	167,280,637	56,584,736	176,437,081	87,011,745	750,166,834
Fuel (ASM) cost effect	2,991,035	13,822,849	20,359,221	23,041,256	13,371,442	109,350,508	29,419,071	210,577,880
Passenger-related effect	56,810,491	5,311,971	160,670,327	142,734,270	-63,957,517	188,402,887	303,736,764	950,623,757
TOTAL	**83,993,646**	**159,396,602**	**293,578,308**	**333,056,163**	**5,998,661**	**474,190,476**	**420,167,580**	**1,911,368,472**
CAPACITY UNDERUTILIZATION COMPONENT 2001-2003								
Unused capacities	2,139,670	-583,709,853	1,259,403	-946,583,580	-138,564,355	-156,183,386	-106,042,848	-1,841,908,757
Available capacities	-190,069,839	-224,132,872	480,053,707	1,460,497,163	711,275,204	2,435,963,858	1,238,996,270	5,710,889,146
Used capacities	139,500,579	202,026,324	-298,061,677	-1,002,067,784	-513,324,575	-1,418,489,068	-750,982,716	-3,547,436,803
TOTAL	**-48,429,590**	**-605,816,401**	**183,251,434**	**-488,154,201**	**59,386,273**	**861,291,403**	**381,970,707**	**321,543,586**

Table 6b: Strategic Variance Analysis 2004-2006

	Alaska	American	Continental	Delta	Northwest	United	US Airways	Composite
GROWTH COMPONENT	**2004-2006**							
Revenue effect	453,691,878	2,811,775,915	2,496,491,053	1,531,735,627	553,888,048	1,727,294,826	-66,291,108	9,855,630,117
Fuel cost effect	-66,403,583	-388,327,209	-358,212,552	-171,911,836	-84,464,216	-248,461,285	7,094,394	-1,317,325,858
Flight-related cost effect	-175,151,540	-1,375,345,063	-1,061,955,929	-813,147,817	-227,598,043	-890,324,602	33,377,004	-4,780,185,949
Passenger-related effect	-139,294,499	-768,232,901	-728,649,836	-390,941,719	-191,634,632	-514,421,314	17,788,048	-2,820,943,581
TOTAL	**72,842,256**	**279,870,742**	**347,672,736**	**155,734,255**	**50,191,158**	**74,087,625**	**-8,031,663**	**937,174,729**
PRICE-RECOVERY COMPONENT 2004-2006								
Revenue effect	211,439,122	2,278,247,085	3,180,486,947	1,604,370,373	2,817,239,952	4,208,835,174	1,380,200,108	15,333,774,883
Fuel cost effect	-471,710,024	-3,828,438,185	-1,853,965,777	-2,920,895,535	-2,246,447,729	-2,841,063,847	-1,007,233,236	-15,222,020,603
Flight-related cost effect	-133,242,925	865,320,879	-1,671,102,977	503,537,331	-700,464,092	-1,029,314,359	-158,519,829	-2,032,146,563
Passenger-related effect	59,044,396	436,067,853	25,400,970	-160,708,624	353,833,643	687,418,915	217,983,665	1,493,693,325
TOTAL	**-334,469,432**	**-248,802,368**	**-319,180,837**	**-973,696,455**	**224,161,774**	**1,025,875,882**	**432,430,708**	**-426,698,958**
PRODUCTIVITY COMPONENT 2004-2006								
Fuel cost effect	50,035,532	481,709,093	204,174,231	365,698,506	194,445,736	87,427,468	56,814,411	1,508,342,435
Fuel (ASM) cost effect	67,859,727	560,049,736	212,520,098	251,902,660	313,814,762	340,760,327	105,158,016	1,842,933,707
Passenger-related effect	48,306,103	246,734,048	268,723,866	879,725,343	8,554,989	269,628,399	168,608,287	2,121,185,256
TOTAL	**166,201,363**	**1,288,492,877**	**685,418,195**	**1,497,326,509**	**516,815,487**	**697,816,193**	**330,580,715**	**5,472,461,399**
CAPACITY UNDERUTILIZATION COMPONENT 2004-2006								
Unused capacities	-40,752,430	214,467,764	-378,268,935	134,235,787	-125,392,998	-224,154,281	-44,119,994	-481,362,397
Available capacities	-131,982,297	-649,794,077	-1,016,842,088	-438,742,912	164,855,537	-459,679,021	335,692,238	-2,470,754,722
Used capacities	175,151,540	1,375,345,063	1,061,955,929	813,147,817	227,598,043	890,324,602	-33,377,004	4,780,185,949
TOTAL	**2,416,813**	**940,018,750**	**-333,155,094**	**508,640,691**	**267,060,581**	**206,491,299**	**258,195,240**	**1,828,068,830**

Table 6c: Strategic Variance Analysis 2007-2009

	Alaska	American	Continental	Delta	Northwest	United	Composite
GROWTH COMPONENT	**2007-2009**						
Revenue effect	76,392,142	-2,746,117,173	247,721,124	322,069,175	-1,788,986,906	-2,792,013,981	-6,782,251,227
Fuel cost effect	-20,341,412	681,059,676	-54,221,482	-75,585,266	459,271,131	662,631,241	1,631,023,084
Flight-related cost effect	-30,956,254	1,101,536,116	-111,433,874	-145,802,625	669,969,292	1,274,484,766	2,898,030,959
Passenger-related effect	-18,566,661	590,939,477	-49,027,225	-61,239,564	428,428,256	512,292,668	1,390,268,958
TOTAL	**6,527,814**	**-372,581,904**	**33,038,544**	**39,441,720**	**-231,318,227**	**-342,605,306**	**-862,928,226**
PRICE-RECOVERY COMPONENT 2007-2009							
Revenue effect	237,099,858	151,015,173	-896,725,124	385,372,825	97,349,906	-182,607,019	-107,178,773
Fuel cost effect	103,408,138	5,602,930	114,270,960	-600,032,058	595,433,020	522,238,504	669,748,078
Flight-related cost effect	-202,025,261	-1,440,766,152	-39,062,189	-719,963,590	-868,515,032	-363,159,189	-3,749,230,763
Passenger-related effect	-9,109,301	-377,711,018	-272,718,665	-405,034,217	-373,895,922	-227,871,310	-1,598,991,366
TOTAL	**129,373,433**	**-1,661,859,067**	**-1,094,235,018**	**-1,339,657,040**	**-549,628,027**	**-251,399,014**	**-4,785,652,825**
PRODUCTIVITY COMPONENT 2007-2009							
Fuel cost effect	85,057,117	8,308,068	141,677,759	-118,679,257	227,211,753	50,184,026	544,457,269
Fuel (ASM) cost effect	19,440,806	31,884,475	28,810,763	200,305,717	-24,843,792	-9,110,740	188,753,647
Passenger-related effect	81,661,963	23,640,541	223,950,890	359,075,781	386,617,666	178,274,642	1,198,430,408
TOTAL	**186,159,886**	**63,833,084**	**394,439,412**	**440,702,242**	**588,985,628**	**219,347,928**	**1,931,641,323**
CAPACITY UNDERUTILIZATION COMPONENT 2007-2009							
Unused capacities	-52,444,574	-345,352,446	-8,320,470	-154,375,462	-168,581,670	-80,286,845	-828,939,806
Available capacities	11,477,186	1,439,083,450	-57,020,340	232,399,916	729,066,589	1,527,048,003	4,017,372,492
Used capacities	30,956,254	-1,101,536,116	111,433,874	145,802,625	-669,969,292	-1,274,484,766	-2,898,030,959
TOTAL	**-10,011,134**	**-7,805,112**	**46,093,063**	**223,827,079**	**-109,484,373**	**172,276,392**	**290,401,727**

Table 9 provides the strategic variance analysis for Alaska Airlines for the last year of the long-term strategic plan. Other network carriers are not included because the group changed yet again with the merger of Northwest Airlines into Delta. The analysis shows that Alaska experienced continued and significant growth in profitability due to growth in the market. In 2007, Alaska began adding service to Hawaii, and by 2010, that market represented 15% of its total network (Ayer 2011).

The price-recovery component for 2010 shows a contribution to net operating profits of $49.5 million, achieved primarily through higher airfares. Productivity gains contributed $68 million, primarily due to fuel cost savings and passenger-related savings. In addition, Alaska Airlines made much better use of capacity, achieving a gain in profitability of $69.3 million. According to Ayer (2010), Alaska reduced its capacity on routes with low demand while increasing capacity on routes with higher demand, particularly the routes to Hawaii.

On the surface, it would appear as if the Alaska 2010 strategic plan was a huge success. However, it is not sufficient to look at the performance of Alaska Airlines in a vacuum. Benchmarking against the other network air carriers is necessary to determine just how successful the plan has been. Tables 7a, 7b, and 7c provide rankings for the network carriers, after normalizing the data for size differences by dividing by RPMs. Alaska Airlines ranked first in the growth component in the earliest period, second in the middle period, and third in the last three-year period. This analysis shows that for most of the time, Alaska Airlines was among the leaders in increased market share as air travel recovered and grew after the tragedy of 9/11.

The price-recovery component directly corresponds to Porter's (1980) product differentiation strategy. It is interesting to note that Alaska Airlines ranked first during the three years ending December 31, 2003, and December 31, 2009. But for the three years ending December 31, 2006, it ranked last. The productivity component directly corresponds to Porter's (1980) cost leadership strategy. Alaska ranked second in the first two, three-year periods, and improved to a first place ranking in the third, three-year period. Its consistently high ranking on this component suggests that Alaska 2010 was focused primarily on cutting costs and becoming the low-cost leader in the industry. However, it is also evident that management is using a blended strategy, since it ranked first in price-recovery for two of the three periods.

Alaska Airlines ranked fifth and sixth over the nine years in terms of capacity underutilization. This suggests that managing capacity was not a major focus of the Alaska 2010 strategic plan, or, if it was, then the competition continues to do a better job than Alaska at managing capacity. Going forward, this also suggests that management may be able to increase future profitability by improving its use of capacity.

As shown in Tables 6a, 6b, and 6c, Alaska Airlines experienced increases in annual operating profits due to growth in the market. The growth component, however, is impacted by exogenous factors as well as endogenous factors. Horngren et al. (2012) provide an adjustment to the growth component to estimate how much of the growth component is due to management's strategic decisions (endogenous factors). The estimate is based on the overall growth in the market, in this case, the composite figures for the network carriers. For example, if the market grew by 50%, then 50% growth is assumed for Alaska Airlines. Any growth above and beyond 50% is assumed to be endogenous.

Table 8a shows that nearly 150% of Alaska's growth is attributable to endogenous factors. Overall, the market actually decreased by more than 10% for the period, yet Alaska grew its market share by 21.42%. Similarly, management's initiatives contributed 39.3% to Alaska's growth in 2006, as shown in Table 8b, and 352% in 2009, as shown in Table 8c. In 2009, the overall market decreased by 7.64%, yet Alaska grew its market by 3%. Thus, in all three periods, management's strategic decisions had a positive impact on growth in the market. This result is consistent with Alaska's high ranking on productivity, as companies that follow a low cost strategy tend to exhibit growth in market share.

Table 7a: Normalized Strategic Variance Analysis 2001-2003

	Alaska	American	Continental	Delta	Northwest	United	US Airways	Composite
GROWTH COMPONENT 2001-2003	1	2	3	6	4	5	7	
Revenue effect	26,025,565	4,522,050	-13,983,430	-29,705,485	-21,537,181	-33,781,010	-47,303,405	-18,821,496
Fuel cost effect	-4,230,555	-547,906	1,974,653	3,430,863	3,439,571	4,039,619	5,772,118	2,408,204
Flight-related cost effect	-9,585,337	-1,683,859	5,240,754	11,242,094	7,499,887	13,660,963	19,910,108	7,231,711
Passenger-related effect	-8,138,144	-1,338,449	4,069,603	8,105,999	6,997,270	9,561,408	13,490,209	5,480,470
TOTAL	**4,071,529**	**951,837**	**-2,698,421**	**-6,926,529**	**-3,600,453**	**-6,519,019**	**-8,130,970**	**-3,701,112**
_PRICE-RECOVERY COMPONENT 2001-2003	1	4	3	5	2	7	6	
Revenue effect	-7,644,538	-10,471,465	-17,593,194	17,164,779	-4,364,534	-23,362,908	-16,845,020	-8,670,633
Fuel cost effect	1,630,340	-2,473,360	-145,533	-3,597,796	642,455	-3,088,968	1,658,452	-1,667,952
Flight-related cost effect	342,346	-13,038,928	69,661	-30,782,225	-6,890,515	-4,880,320	-7,715,263	-11,115,697
Passenger-related effect	-722,758	6,356,944	2,186,909	-3,472,688	-477,158	2,891,411	-227,698	1,296,995
TOTAL	**-6,394,611**	**-19,626,808**	**-15,482,157**	**-20,687,929**	**-11,089,751**	**-28,440,786**	**-23,129,529**	**-20,157,286**
PRODUCTIVITY COMPONENT 2001-2003	2	6	3	5	7	4	1	
Fuel cost effect	1,662,284	1,169,061	1,978,921	1,876,704	826,727	1,699,203	2,306,862	1,529,270
Fuel (ASM) cost effect	205,519	115,211	357,972	258,497	195,362	1,053,116	779,961	429,279
Passenger-related effect	3,903,551	44,274	2,825,032	1,601,321	-934,446	1,814,441	8,052,691	1,937,917
TOTAL	**5,771,355**	**1,328,546**	**5,161,924**	**3,736,522**	**87,643**	**4,566,760**	**11,139,513**	**3,896,465**
CAPACITY UNDERUTILIZATION COMPONENT 2001-2003	5	6	3	7	4	2	1	
Unused capacities	147,021	-4,865,133	22,144	-10,619,622	-2,024,483	-1,504,147	-2,811,416	-3,754,867
Available capacities	-13,060,042	-1,868,113	8,440,681	16,385,165	10,392,028	23,459,901	32,848,359	11,642,068
Used capacities	9,585,337	1,683,859	-5,240,754	-11,242,094	-7,499,887	-13,660,963	-19,910,108	-7,231,711
TOTAL	**-3,327,685**	**-5,049,388**	**3,222,071**	**-5,476,551**	**867,658**	**8,294,791**	**10,126,835**	**655,490**

Note: Numbers in shaded areas are rankings, from 1 to 7, of the effect of a component on operating income.

Table 7b: Normalized Strategic Variance Analysis 2004-2006

	Alaska	American	Continental	Delta	Northwest	United	US Airways	Composite
GROWTH COMPONENT 2004-2006	2	3	1	4	5	6	7	
Revenue effect	25,473,465	20,175,983	32,747,227	15,511,530	7,632,226	14,735,230	-1,774,916	17,621,381
Fuel cost effect	-3,728,366	-2,786,454	-4,698,782	-1,740,911	-1,163,863	-2,119,577	189,949	-2,355,314
Flight-related cost effect	-9,834,244	-9,868,830	-13,929,997	-8,234,559	-3,136,157	-7,595,193	893,655	-8,546,737
Passenger-related effect	-7,820,977	-5,512,478	-9,557,920	-3,958,976	-2,640,604	-4,388,432	476,267	-5,043,708
TOTAL	**4,089,879**	**2,008,221**	**4,560,528**	**1,577,085**	**691,602**	**632,028**	**-215,044**	**1,675,622**
PRICE-RECOVERY COMPONENT 2004-2006	7	4	5	6	3	2	1	
Revenue effect	11,871,685	16,347,631	41,719,408	16,247,086	38,819,781	35,904,788	36,954,265	27,416,033
Fuel cost effect	-26,485,131	-27,471,074	-24,319,029	-29,579,230	-30,954,626	-24,236,586	-26,968,237	-27,216,222
Flight-related cost effect	-7,481,199	6,209,136	-21,920,362	5,099,205	-9,651,951	-8,780,889	-4,244,300	-3,633,378
Passenger-related effect	3,315,169	3,129,018	333,192	-1,627,459	4,875,603	5,864,243	5,836,419	2,670,650
TOTAL	**-18,779,475**	**-1,785,289**	**-4,186,791**	**-9,860,398**	**3,088,807**	**8,751,556**	**11,578,146**	**-762,917**
PRODUCTIVITY COMPONENT 2004-2006	2	3	4	1	6	7	5	
Fuel cost effect	2,809,348	3,456,518	2,678,215	3,703,344	2,679,339	745,827	1,521,181	2,696,842
Fuel (ASM) cost effect	3,810,124	4,018,654	2,787,690	2,550,960	4,324,169	2,906,963	2,815,561	3,295,075
Passenger-related effect	2,712,246	1,770,448	3,524,932	8,908,774	117,882	2,300,150	4,514,414	3,792,575
TOTAL	**9,331,718**	**9,245,620**	**8,990,837**	**15,163,077**	**7,121,390**	**5,952,940**	**8,851,157**	**9,784,491**
CAPACITY UNDERUTILIZATION COMPONENT 2004-2006	6	2	7	3	4	5	1	
Unused capacities	-2,288,129	1,538,920	-4,961,868	1,359,375	-1,727,836	-1,912,218	-1,181,294	-860,652
Available capacities	-7,410,418	-4,662,617	-13,338,225	-4,443,047	2,271,605	-3,921,436	8,988,015	-4,417,588
Used capacities	9,834,244	9,868,830	13,929,997	8,234,559	3,136,157	7,595,193	-893,655	8,546,737
TOTAL	**135,697**	**6,745,133**	**-4,370,096**	**5,150,886**	**3,679,926**	**1,761,539**	**6,913,067**	**3,268,497**

Note: Numbers in shaded areas are rankings, from 1 to 7, of the effect of a component on operating income.

Table 7c: Normalized Strategic Variance Analysis 2007-2009

	Alaska	American	Continental	Delta	Northwest	United	Composite
GROWTH COMPONENT 2007-2009	3	4	1	2	6	5	
Revenue effect	4,170,858	-22,445,070	3,188,719	3,202,043	-28,747,399	-27,838,296	-14,086,888
Fuel cost effect	-1,110,600	5,566,562	-697,950	-751,476	7,380,071	6,606,888	3,387,672
Flight-related cost effect	-1,690,150	9,003,278	-1,434,400	-1,449,584	10,765,800	12,707,488	6,019,276
Passenger-related effect	-1,013,703	4,829,975	-631,089	-608,850	6,884,454	5,107,909	2,887,620
TOTAL	**356,406**	**-3,045,255**	**425,279**	**392,133**	**-3,717,074**	**-3,416,010**	**-1,792,321**
PRICE-RECOVERY COMPONENT 2007-2009	1	5	6	4	3	2	
Revenue effect	12,945,178	1,234,305	-11,542,836	3,831,414	1,564,325	-1,820,717	-222,613
Fuel cost effect	5,645,877	45,795	1,470,920	-5,965,576	9,568,069	5,207,076	1,391,082
Flight-related cost effect	-11,030,175	-11,775,935	-502,817	-7,157,947	-13,956,250	-3,620,946	-7,787,237
Passenger-related effect	-497,350	-3,087,177	-3,510,492	-4,026,889	-6,008,169	-2,272,033	-3,321,141
TOTAL	**7,063,531**	**-13,583,012**	**-14,085,225**	**-13,318,999**	**-8,832,025**	**-2,506,621**	**-9,939,909**
PRODUCTIVITY COMPONENT 2007-2009	1	6	3	4	2	5	
Fuel cost effect	4,643,948	67,905	1,823,706	-1,179,921	3,651,087	500,369	1,130,850
Fuel (ASM) cost effect	1,061,429	260,604	370,858	1,991,459	-399,217	-90,840	392,046
Passenger-related effect	4,458,580	193,223	2,882,743	3,569,966	6,212,596	1,777,521	2,489,167
TOTAL	**10,163,957**	**521,732**	**5,077,308**	**4,381,504**	**9,464,466**	**2,187,049**	**4,012,063**
CAPACITY UNDERUTILIZATION COMPONENT 2007-2009	5	4	3	1	6	2	
Unused capacities	-2,863,369	-2,822,698	-107,103	-1,534,816	-2,708,955	-800,515	-1,721,727
Available capacities	626,631	11,762,182	-733,978	2,310,542	11,715,440	15,225,717	8,344,173
Used capacities	1,690,150	-9,003,278	1,434,400	1,449,584	-10,765,800	-12,707,488	-6,019,276
TOTAL	**-546,588**	**-63,794**	**593,320**	**2,225,310**	**-1,759,315**	**1,717,714**	**603,171**

Note: Numbers in shaded areas are rankings, from 1 to 6, of the effect of a component on operating income.

Table 8a: Impact of Endogenous Strategies - Growth Component 2001 (12/31/00) – 2003 (12/31/03)

	RPMs 2001	RPMs 2003	%Δ2001-2003	ENDOGENOUS
Alaska	11,986,220,472.44	14,553,539,641.00	21.42	149.86%
American	116,546,866,300.80	120,299,948,301.92	3.22	431.68%
Continental	62,344,035,830.75	57,577,384,884.77	-7.65	39.61%
Delta	107,817,843,792.25	89,412,207,706.99	-17.07	-37.43%
Northwest	79,204,321,760.92	68,746,644,595.56	-13.20	-19.09%
United	126,906,366,817.78	104,371,719,160.11	-17.76	-39.86%
US Airways	46,870,108,565.97	37,774,319,225.72	-19.41	-44.98%
Composite	551,675,763,540.92	492,735,763,516.07	-10.68	

Endogenous Effect = [%ΔRPMs(2001-2003)$_{\text{Airline i}}$ - %ΔRPMs(2001-2003)$_{\text{Market}}$] / |%ΔRPMs(2001-2003)$_{\text{Airline i}}$|

Table 8b: Impact of Endogenous Strategies - Growth Component 2004 (12/31/03) – 2006 (12/31/06)

	RPMs 2004	RPMs 2006	%Δ2004-2006	ENDOGENOUS
Alaska	14,553,539,641	17,822,404,781	22.46	39.31%
American	120,299,948,302	139,420,782,629	15.89	14.22%
Continental	57,577,384,885	76,302,518,293	32.52	58.09%
Delta	89,412,207,707	98,887,497,017	10.60	-28.58%
Northwest	68,746,644,596	72,674,331,902	5.71	-138.70%
United	104,371,719,160	117,445,990,416	12.53	-8.78%
US Airways	37,774,319,226	37,357,913,286	-1.10	-1339.09%
Composite	492,735,763,516	559,911,438,325	13.63	

Endogenous Effect = [%ΔRPMs(2004-2006)$_{\text{Airline i}}$ - %ΔRPMs(2004-2006)$_{\text{Market}}$] / |%ΔRPMs(2004-2006)$_{\text{Airline i}}$|

Table 8c: Impact of Endogenous Strategies - Growth Component 2006 (12/31/06) – 2009 (12/31/09)

	RPMs 2006	RPMs 2009	%Δ2006-2009	ENDOGENOUS
Alaska	17,822,404,781	18,361,670,904	3.03	352.15%
American	139,420,782,629	122,391,483,735	-12.21	-37.43%
Continental	76,302,518,293	77,768,332,936	1.92	497.92%
Delta	98,887,497,017	100,711,842,838	1.84	515.22%
Northwest	72,674,331,902	62,941,173,546	-13.39	-42.94%
United	117,445,990,416	100,453,973,793	-14.47	-47.23%
Composite	522,553,525,039	482,628,477,752	-7.64	

Endogenous Effect = [%ΔRPMs(2006-2009)$_{\text{Airline i}}$ - %ΔRPMs(2006-2009)$_{\text{Market}}$] / |%ΔRPMs(2006-2009)$_{\text{Airline i}}$|

Table 9: Strategic Variance Analysis Alaska Airlines 2009-2010

	Alaska	Normalized Alaska
GROWTH COMPONENT 2009-2010		
Revenue effect	326,586,654	16,083,578
Fuel cost effect	-57,515,122	-2,832,476
Flight-related cost effect	-143,852,606	-7,084,382
Passenger-related effect	-65,231,740	-3,212,500
TOTAL	**59,987,186**	**2,954,219**
PRICE-RECOVERY COMPONENT 2009-2010		
Revenue effect	94,039,346	4,631,203
Fuel cost effect	-163,054,470	-8,030,026
Flight-related cost effect	96,567,740	4,755,720
Passenger-related effect	21,979,726	1,082,447
TOTAL	**49,532,341**	**2,439,344**
PRODUCTIVITY COMPONENT 2009-2010		
Fuel cost effect	5,392,354	265,560
Fuel (ASM) cost effect	35,155,480	1,731,320
Passenger-related effect	27,478,015	1,353,224
TOTAL	**68,025,849**	**3,350,103**
CAPACITY UNDERUTILIZATION COMPONENT 2009-2010		
Unused capacities	19,325,217	951,719
Available capacities	-93,894,199	-4,624,055
Used capacities	143,852,606	7,084,382
TOTAL	**69,283,624**	**3,412,046**

Table 10a: ASM and RPKm by Aircraft Type - 2003
(A Prefix = Alaska, H Prefix = Horizon, T Prefix = Total (A + H), ST Prefix = Summary Total)

Airline	Aircraft Type	%AASM	%ARPM	%HASM	%HRPM	%TASM	%TRPM	%STASM	%STRPM
Alaska	**Boeing 737-700/700LR**	19.46%	20.21%			17.33%	18.16%		
Alaska	**Boeing 737-400**	38.55%	37.44%			34.33%	33.65%		
Alaska	**Boeing 737-200C**	2.91%	2.16%			2.59%	1.94%		
Alaska	**Boeing 737-900**	12.42%	12.97%			11.06%	11.66%		
Alaska	**McDonnell Douglas DC9 Super 80/MD81/82/83/88**	26.66%	27.22%			23.74%	24.46%	89.05%	89.87%
Horizon	**De Havilland DHC8-400 Dash-8**			32.64%	31.57%	3.57%	3.20%		
Horizon	**De Havilland DHC8-200Q Dash-8**			20.96%	20.81%	2.29%	2.11%		
Horizon	**Fokker F28-4000/6000 Fellowship**			0.34%	0.38%	0.04%	0.04%		
Horizon	**Canadair RJ-700**			46.06%	47.23%	5.04%	4.78%	10.94%	10.13%

Data Source: U. S. Department of Transportation, Research and Innovative Administration, Bureau of Transportation Statistics, *TranStats Database*, Washington, D. C., 2003

Table 10b: ASM and RPKm by Aircraft Type - 2006
(A Prefix = Alaska, H Prefix = Horizon, T Prefix = Total (A + H), ST Prefix = Summary Total)

Airline	Aircraft Type	%AASM	%ARPM	%HASM	%HRPM	%TASM	%TRPM	%STASM	%STRPM
Alaska	Boeing 737-700/700LR	19.93%	20.22%			17.24%	17.57%		
Alaska	Boeing 737-800	11.24%	12.20%			9.72%	10.60%		
Alaska	Boeing 737-400	32.04%	30.35%			27.71%	26.37%		
Alaska	Boeing 737-200C	1.13%	1.04%			0.98%	0.91%		
Alaska	Boeing 737-900	15.30%	15.73%			13.23%	13.66%		
Alaska	McDonnell Douglas DC9 Super 80/MD81/82/83/88	20.37%	20.46%			17.62%	17.77%	86.50%	86.88%
Horizon	De Havilland DHC8-400 Dash-8			36.01%	35.78%	4.86%	4.70%		
Horizon	De Havilland DHC8-200Q Dash-8			14.67%	14.62%	1.98%	1.92%		
Horizon	Canadair RJ-700			49.32%	49.60%	6.66%	6.51%	13.50%	13.13%

Data Source: U. S. Department of Transportation, Research and Innovative Administration, Bureau of Transportation Statistics, *TranStats Database*, Washington, D. C., 2006

Table 10c: ASM and RPKm by Aircraft Type - 2009
(A Prefix = Alaska, H Prefix = Horizon, T Prefix = Total (A + H), ST, Prefix = Summary Total)

Airline	Aircraft Type	%AASM	%ARPM	%HASM	%HRPM	%TASM	%TRPM	%STASM	%STRPM
Alaska	Boeing 737-700/700LR	11.70%	11.48%			10.24%	10.15%		
Alaska	Boeing 737-800	55.90%	57.51%			48.93%	50.84%		
Alaska	Boeing 737-400	19.21%	17.49%			16.82%	15.46%		
Alaska	Boeing 737-900	13.19%	13.52%			11.55%	11.95%	87.54%	88.40%
Horizon	De Havilland DHC8-400 Dash-8			59.76%	57.39%	7.44%	6.65%		
Horizon	De Havilland DHC8-200Q Dash-8			0.01%	0.01%	0.0013%	0.0013%		
Horizon	Canadair RJ-700			40.23%	42.60%	5.01%	4.94%	12.45%	11.59%

Data Source: U. S. Department of Transportation, Research and Innovative Administration, Bureau of Transportation Statistics, *TranStats Database*, Washington, D. C., 2009

THE INTERACTION BETWEEM ALASKA AND HORIZON AIR INDUSTRIES AND THE IMPACT ON SVA RESULTS

Although the focus of this research is Alaska Airlines, the Alaska 2010 initiative impacted both airlines in the group, Alaska Airlines and Horizon Air Industries. During the period of this study, it is possible that Alaska Airlines shifted routes, frequencies of flights, and aircraft to its regional affiliate, Horizon Air Industries. If this occurred to a significant degree, then there might be an important impact in terms of the underlying drivers of the results of the strategic variance analysis.

ASMs and RPMs by aircraft type for both carriers were examined to try and detect route interactions between the two airlines. Conceptually, if such an interaction were of significant magnitude, then one would see a larger share of ASMs and RPMs being flown by the aircraft types of the regional affiliate airline. Table 10 shows virtually no change in ASMs and RPMs by aircraft types flown by Alaska Airlines versus those flown by Horizon Air Industries for the years ending in 2003, 2006, and 2009 (the end points of each of the periods used in the SVA analysis). Instead, Alaska Airlines phased out its usage of McDonnell Douglas aircraft in favor of more efficient ones from the single Boeing 737 family. Horizon Air Industries phased out its Fokker and De Havilland DHC8-200Q Dash-8 airplanes in favor of the more efficient De Havilland DHC8-400 Dash-8 aircraft.

In addition, the annual reports of the Alaska Air Group were examined for each year in the study. Typically, in the letter to shareholders, the CEO discusses progress made in the strategic plan for the preceding year. In only one year, 2007, was there any mention of a shift in service between the two airlines. In that year, Alaska Airlines contracted with Horizon Air Industries for the use of some 70-seat Canadair RJ-700 aircraft for certain routes for which Alaska's Boeing 737 jets were too large to be profitable. Thus, it appears that for the entire period of the study, any interaction effects were minimal.

SUMMARY AND CONCLUSIONS

In 2003, Alaska Air Group embarked on a long-term strategic plan to transform the company. Management referred to the plan in annual reports to stockholders in 2003 and in subsequent years, marking their successes and further needs for improvement. In fact, the plan appeared to be highly successful based on the 2010 annual report to stockholders. Strategic variance analysis provides a means to assess the plan and to categorize management's efforts in terms of Porter's (1980) long-term strategies for business success. This paper examines Alaska Airlines' performance in three-year time windows from 2001 to 2003, 2004 to 2006, and 2007 to 2009. In addition, we examine 2010, the last year of the strategic plan.

Strategic variance analysis shows that Alaska Airlines focused primarily on growing its share of the market and on productivity gains by cutting costs. In later years, they also followed a product differentiation strategy, raising air fares sufficiently to cover increased costs for such a strategy. Finally, they made changes in their routes to achieve greater profitability through better use of capacity.

The success of the plan may also be measured by comparison with the other network carriers. That analysis revealed that by 2009, Alaska ranked first in both productivity and price-recovery, as well as third in growth in market share. In sum, it appears that management delivered on its forecast in the 2003 annual report that 2010 would be a year where they could "look back with great pride at how we transformed ourselves" (Ayer 2004).

APPENDIX
Calculation of Strategic Variances from Year i to Year j

The Growth Component

1. Airline Revenues

[***Revenue effect of the Growth Component (i.e., lower expected revenue due to lower RPM)***]

Variance = {Year i revenue/RPM} * {Year j RPMs – Year i RPMs}

2. Fuel Costs

[***Fuel cost effect of the Growth Component (i.e., lower expected fuel costs due to lower RPMs)***]

Variance = {Year i fuel cost/gallon} * {Year i gallons used per ASM} * {Year i actual ASMs – Year j budgeted ASMs}

3. Flight-related Costs

[***Flight-related cost effect of the Growth Component (i.e., lower expected flight-related costs due to lower RPMs)***]

Variance = {Year i cost/ASM} * {Year i passenger load factor} * {Year i actual ASMs – Year j budgeted ASMs}

4. Passenger-related Costs

[***Passenger-related cost effect of the Growth Component (i.e., lower expected passenger-related costs due to lower RPMs)***]

Variance = {Year i cost/passenger} * {Year i revenue passengers – Year j budgeted revenue passengers}

The Price-Recovery Component

1. Airline Revenues

[***Revenue effect of the Price-Recovery Component (i.e., higher revenue due to higher airfares)***]

Variance = {Year j RPMs} * {Year j revenue/RPM – Year i revenue/RPM}

2. Fuel Costs

[***Fuel cost effect of the Price-Recovery Component (i.e., higher costs due to higher fuel prices)***]

Variance = {Year j budgeted ASMs} * {Year i gallons used/ASM} * {Year i fuel cost/gallon – Year j fuel cost/gallon}

3. Flight-related Costs

[***Flight-related cost effect of the Price-Recovery Component (i.e., higher costs due to higher flight-related costs per ASM)***]

Variance = {Year j passenger load factor} * {Year j actual ASMs} * {Year i cost/ASM – Year j cost/ASM}

4. Passenger-related Costs

[***Passenger-related cost effect of the Price-Recovery Component (i.e., higher costs due to higher costs per passenger)***]

Variance = {Year j budgeted revenue passengers} * {Year i cost/passenger – Year j cost/passenger}

The Productivity Component

1. Fuel Costs (a)

[***Fuel cost effect of the Productivity Component (i.e., lower costs due to lower fuel usage per gallon)***]

Variance = {Year j fuel cost/gallon} * {Year j budgeted ASMs} * {Year i gallons used /ASM – Year j gallons used/ASM}

2. Fuel Costs (b)
[*Fuel (ASM) cost effect of the Productivity Component (i.e., lower costs due to higher passenger load factor)*]
Variance = {Year j fuel cost/gallon} * {Year j gallons used/ASM} * {Year j budgeted ASMs – Year j actual ASMs}
3. Passenger-related costs
[*Passenger-related cost effect of the Productivity Component (i.e., lower costs due to higher miles per passenger)*]
Variance = {Year j cost/passenger} * {Year j budgeted revenue passengers – Year j revenue passengers}

The Capacity Underutilization Component
1. Flight-related costs (a)
[*Changes in flight-related costs relating to unused capacities (i.e., higher unit costs to acquire capacity that is unused)*]
Variance = {Year j actual ASMs – Year j RPMs} * {Year i cost/ASM – Year j cost/ASM}

2. Flight-related costs (b)
[*Changes in flight-related costs of available capacities (i.e., lower underutilization due to decrease in available capacity)*]
Variance = {Year i cost/ASM} * {Year i actual ASMs – Year j actual ASMs}

3. Flight-related costs (c)
[*Changes in flight-related costs of used capacities (i.e., higher underutilization due to decrease in capacity used)*]
Variance = {Year i cost/ASM} * {Year j RPMs – Year i RPMs}

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Efficiency Benchmarking of North American Airports: Comparative Results of Productivity Index, Data Envelopment Analysis and Stochastic Frontier Analysis

by Zhuo (Frank) Lin, YapYin Choo, and Tae Hoon Oum

Using three common methodologies for measuring airport efficiency, namely the productivity index method, Data Envelopment Analysis (DEA) method, and stochastic frontier analysis (SFA) method, this study examines the efficiency performances of 62 Canadian and U.S. airports. Unlike most previous studies, this study includes aeronautical and non-aeronautical outputs of airports as they are inexplicably tied to each other in airport production. The empirical results reveal that the efficiency scores and rankings measured by these alternative methods are quite similar to each other in the top 15 and bottom 15 ranked airports, whereas considerable differences exist among the airports in the middle range. We also found that the percentage of non-aeronautical revenue, passenger volume, average aircraft size, percentages of international and connecting traffic significantly affect our airport efficiency estimates in all of the three alternative approaches used.

INTRODUCTION

Airports have substantial market power over the majority of local traffic and airlines. In many North American cities, airlines,[1] passengers, and other airport users have limited choices when selecting airports. Regulatory, geographical, economic, social, and political constraints all tend to hinder competition between airports. Therefore, unlike airline markets, competitive pressure cannot be relied on to exert enough pressures for airport managers to pay serious attention to improve productivity and efficiency. However, by exposing inefficient airports to their stakeholders, the public and their regulatory authorities,[2] airport benchmarking helps spur competitive forces and shake up conventional thinking on airport efficiency performance.

The evolution of airport ownerships toward privatization and commercialization naturally leads airport managers to seek ways to gain insights into their operations and improve performance by benchmarking themselves against other airports. As benchmarking identifies the best practice standards for operations and services, it provides guidelines for airport managers to improve performance and deal with delays and congestion. This is a major reason why recently the ACI-North America has started to do benchmarking performance of its member airports, although its benchmarking results are not public and are used for internal purposes.

During the past two decades, there has been a plethora of research on airport benchmarking. Liebert and Niemeier (2010) reviewed and summarized literature on airport benchmarking, and found that there are many inconclusive or conflicting findings, including the effects of ownership, privatization, and size on airport performance.[3] The discrepancies in the results of airport benchmarking may due to the differences, including methodology and underlying assumptions, sample data and years, variables used for inputs, outputs and heterogeneities among the airports, such as ownership, regulatory framework, and other factors beyond management control.

Most studies in airport benchmarking utilize a single method to measure airport efficiency. So far, only a few studies have measured efficiencies by using different methodologies. Cullinane et al. (2006) applied data envelopment analysis (DEA) and stochastic frontier analysis (SFA) in the container port industry and found that there is a high degree of correlation between the results of the two approaches.

Coelli and Perelman (1999) compared three alternative methodologies: (1) parametric frontier using linear programming approach; (2) parametric frontier using corrected OLS method (including SFA); and (3) non-parametric piece-wise linear frontier using DEA. When applying them to a pool of data of 17 European railways from 1988 to 1993, the technical efficiencies emerging from the three methods displayed no substantial differences, with positive and significant correlations between each other. The authors claimed that a researcher could safely select one of these methods without too much concern for their choice having a large influence upon results.

For the aviation industry, Windle and Dresner (1995) compared seven methods of productivity measurement using 1983 U.S. airline data, and concluded that: "carrier rankings from the cost function decomposition bear no relationship to the rankings for the gross measure of productivity." This finding thus supports the need for second stage (regression) analysis to control for differences in output characteristics, especially when non-parametric methods such as TFP and DEA are used. Pels et al. (2001) compared the efficiency results of European airports measured from DEA and SFA. Unfortunately, this paper applies these two measurement methods separately to each of airside operations and terminal side operations as if they are two independent businesses and do not include non-aeronautical revenue outputs. Based on the dataset of European airports, the results emerging from the two methods were reasonably consistent despite the fact that SFA produced less dispersed efficiency scores.

As stated in Oum et al. (1992), productivity studies in the transportation industry using different measures of outputs and inputs cannot be compared directly with each other. To the best of our knowledge, no research has been directed toward the comparison between different methodologies and their empirical results in airport benchmarking. This study aims to offer the first step toward filling this gap. More importantly perhaps, to the knowledge of the authors, no airport performance benchmarking paper published so far treated both aeronautical operations and non-aeronautical operations within a single airport firm context. The omission of non-aeronautical revenue outputs invites bias against the airports that have tried to generate more revenue from commercial and business activities so that they could pass on the benefits to airlines, passengers, shippers, and other airport users by lowering airside charges. The size of the bias would be enormous if it is considered that major airports generate anywhere between 30% and 70% of their total revenues from non-aeronautical services while in general airports' inputs are inseparable between those used to generate aeronautical revenues and others for generating non-aeronautical services from airports' available accounting data.

The main objective of this study is to review and empirically compare the results of the three key methodologies employed in measuring airport efficiency, namely, productivity index method, DEA method, and SFA method using comprehensive output data, which include both aeronautical services outputs and non-aeronautical services outputs. The dataset consists of a cross-section of 55 U.S. airports and seven Canadian airports in 2006. There are several reasons for choosing North American airports. First, North America is currently the largest air transport market in the world. Second, the ownership and regulatory framework of North American airports are relatively consistent: airports are owned and/or operated either by government agencies or by airport authorities. Third, there are extensive and reliable data for airports in North America, which make it possible to conduct a valid study using relatively consistent data.

The rest of the study is organized as follows: the next section reviews the three methodologies of efficiency measurement (Index Number Method, DEA, and SFA), followed by the description of the data used in this study. This is followed by the estimation results and comparisons between the efficiencies scores and rankings stemming from the three methods, and the conclusion.

METHODOLOGIES ON PRODUCTIVITY AND EFFICIENCY MEASUREMENT

Productivity of a firm is the ratio of the output(s) produced to the input(s) used to produce the output(s) (Coelli et al. 2005). Hensher and Walters (1993) asserted that there are three quantitative methods to examine the productivity and efficiency among government enterprises, namely: (1) Non-parametric Index Number Method, (2) DEA, and (3) SFA. Liebert and Niemeier (2010), Forsyth (2000) and Oum et al. (2008) have provided an overview of the quantitative methods used for airport productivity and efficiency measurement. Since details of each of these methods are available in the papers just cited and many other sources, this section will only briefly describe and compare the major properties of the three methods.

Index Number Method

As a non-parametric approach, Index Number Method directly defines productivity as output index over input index. The method is easy to conduct for single output and input firms. However, airports utilize multiple inputs such as labor, capital, and other resources to produce various services for both airlines and passengers. Similar to Oum et al. (2006) in the airport industry and Obeng et al. (1992) in public transit systems, this paper uses the multilateral index number method proposed by Caves, Christensen, and Diewert (1982) to aggregate inputs and outputs. The total factor productivity of a firm is calculated as the ratio of aggregate output index over aggregate input index.

Unlike other inputs, capital cost is usually quasi-fixed and cannot be easily adjusted in the short-to-medium term. It is a major challenge to measure capital inputs and costs accurately, as well as to collect consistent and comparable data on capital expenditures. This is because 1) expenditures on capital equipment, buildings, and other infrastructural costs such as runways and terminals are often invested over many years and may be "hidden" in the explicit (or published) costs; 2) facilities at airports may be built and operated by airlines or other enterprises; and 3) the sources of financing and accounting systems vary among airports. Other reasons are 1) some direct and indirect subsidies are not in financial statements, 2) book value data do not resemble replacement value of the capital inputs, and 3) taxation and interest rates vary across states and cities. In the early stage of the ATRS (2001-2011) airport benchmarking, the task force examined the book values of capital accounts of U.S. and Canadian airports, and concluded that those capital accounting data are not comparable at all across airports, and cannot be relied on for any valid study. Consequently, the task force decided to focus on measuring and comparing just the operating efficiency and variable input costs of the airports, excluding capital inputs from their analysis.[4]

Following the well-known procedure devised by Caves, Christensen and Diewert (1982), the variable factor productivity (VFP) model used in this study is computed as follows:

$$\ln VFP_k - \ln VFP_j = (\ln Y_k - \ln Y_j) - (\ln X_k - \ln X_j) = \sum_i \frac{R_{ik} + \overline{R}_i}{2} \ln \frac{Y_{ik}}{\tilde{Y}_i} - \sum_i \frac{R_{ij} + \overline{R}_i}{2} \ln \frac{Y_{ij}}{\tilde{Y}_i} \quad (1)$$

$$- \sum_i \frac{W_{ik} + \overline{W}_i}{2} \ln \frac{X_{ik}}{\tilde{X}_i} + \sum_i \frac{W_{ij} + \overline{W}_i}{2} \ln \frac{X_{ij}}{\tilde{X}_i}$$

where

FP_k is the productivity of k^{th} firm; Y_{ik} and X_{ik} represent the i^{th} output and input of the k^{th} firm respectively; R_{ik} and W_{ik} are the weights for the i^{th} output and input of the k^{th} firm, respectively; A bar over weights represents sample arithmetic mean, while a tilde demonstrates geometric mean.

As implied from equation (1), the VFP index is formed by a series of binary comparisons between each observation and the sample mean. Ideally, revenue and cost elasticities should be used for output and input, respectively. However, as those numbers are usually not obtainable for most industries, including airports, Diewert (1992) suggests using revenue and cost shares as approximations. This adjustment comes with further assumptions on constant returns to scale (CRS) across all outputs.[5]

Data Envelopment Analysis (DEA)

DEA is a non-parametric frontier method and originated from a study in operations research, and was first proposed by Charnes et al. (1978). DEA uses linear programming to construct a piecewise linear "efficient frontier" that envelops Decision-Making Units (DMUs) or firms based on outputs and input quantities. Efficiency indices are then calculated relative to this frontier.

The model is presented with *n* units with *s* outputs denoted by *Y*, and *m* inputs denoted by *X*. For technical efficiency,[6] the following linear programming problem is solved under the assumption of constant returns to scale, i.e., the CCR model developed by Charnes et al. (1978):

(2) $\mathrm{Min}_{\theta,\lambda}\ \theta,\ \textit{subject to}\ \theta x_i - X\lambda \geq 0,\ Y\lambda - y_i \geq 0,\ \lambda \geq 0$

Where, θ is a scalar that indicates the radial contraction of all inputs, hence the technical efficiency (TE) score. λ is the weight of the efficient peers in the reference unit. The x_i's are the individual inputs and y_i the outputs for the *i*th firm. *X* and *Y* represent all input and output matrices.

The BCC model as introduced by Banker et al. (1984) can handle variable returns to scale (RTS) by adding the following constraint to the original CCR model.[7]

(3) $e'\lambda=1$

Where, *e* is a vector of one. The paper uses the CCR model with constant returns to scale in the first stage because the resulting (gross) DEA efficiency measures are more directly comparable with the (gross) VFP, which is computed assuming constant returns to scale as discussed previously. The second stage analysis controls for variable returns to scale by including an output scale variable in the regression.

The DEA method distinguishes between input-oriented and output-oriented models. This study uses the input-oriented model because most previous studies, including Abbott and Wu (2002) and Pels et al. (2001, 2003), use it, and it is a plausible assumption that airports have more control over their inputs than outputs. Since air travel demand is derived demand depending directly on economic activities, airports have less control in generating aeronautical outputs (ATMs, air passenger, and air cargo volumes) than adjusting for variable inputs.[8]

Stochastic Frontier Analysis (SFA)

Different from the productivity index number and DEA, SFA specifies the form of a production or cost function and identifies the inefficiency as a stochastic disturbance. Originally introduced by Aigner et al. (1976), the general form of stochastic frontier production function can be specified as follows:[9]

(4) $Yi = f(xi;\beta)\exp(Vi - Ui)$

Where, Y_i represents the output of the *i*th firm; $f(x_i;\beta)$ is the deterministic core function of an input vector x_i, and an unknown parametric vector β; V_i is a normally distributed random variable that represents the effects of unobservable explanatory variables and random shocks. U_i is a non-negative random variable representing inefficiency, and it is assumed to follow either half-normal, exponential, or gamma distribution.

As implied from equation (4), SFA explains output by a vector of inputs and a stochastic disturbance, which consists of two parts: a stochastic inefficiency, U_i and a traditional 'noise' term, V_i. While V_i could be either positive or negative, U_i is always positive.

For the deterministic part of efficiency, this study uses a translog specification, and as such, our SFA-production function can be written as follows:

$$(5)\quad \ln Yi = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_j + \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{jk} \ln X_j \ln X_k + (V_i - U_i)$$

Where, Y_i is aggregate output index for airport i; X_j is the jth input; V_i is assumed to follow the distribution $N(0, \sigma^2 V)$; U_i is assumed to follow $N(\mu, \sigma^2 U)$ where $\mu \geq 0$. The technical efficiency of airport i is then calculated as the ratio of its mean output to the input if it uses inputs most efficiently.

$$(6)\quad TE_i = \frac{E(Y_i \mid \hat{U}_i, X_i)}{E(Y_i \mid U_i = 0, X_i)} = \exp(-U_i)$$

The SFA production function is estimated by using the input quantity indices (labor input and soft cost input) and the output quantity index (aggregated using the multilateral index procedure discussed in the Index Number Method section).

Comparison of Methodologies

Table 1 summarizes and compares key features of the three alternative methods. The index number method assumes that firms are allocatively efficient and under constant returns to scale.[10] In contrast, DEA and SFA assume the continuity and convexity of the production set. SFA further assumes a particular form of inefficiency distribution: usually one of half-normal, exponential, and gamma distribution. As for data requirement, the productivity index number method demands the highest level of data in general.

All three methods have difficulty in precisely measuring capital costs, the DEA method allows for using physical measures of capital inputs such as terminal size, number and/or length of runway as approximation of capital inputs. The DEA method is thus easy to use with less demanding data. However, DEA efficiency index lacks "transitivity," as DEA airport efficiency rankings can change substantially as one adds or drops one or more airports from the sample.[11] In comparison, index number methods preserve the relative index values and rankings, even when one adds or drops one or more airports from the sample.

As the only parametric method, SFA involves a specification of frontier function, which enables it to conduct hypotheses tests and distinguish the sources of efficiency growth. Furthermore, as SFA does not assume that all firms are efficient, it allows the existence of systemic inefficiency in the error terms, and does not restrict the combined error term (which includes inefficiency distribution) to be assumed independently and identically distributed (i.i.d.). However, because use of SFA requires rigorous theoretical concept and complex computation, it is difficult to communicate the method to industry executives and practitioners.

Table 1: Comparison of Index Number Method, DEA and SFA

	Index Number Method	DEA	SFA
Assumption	• CRS • Allocative efficiency	• Continuous and convex production set	• Inefficiency distribution • Continuous and convex production set
Minimum Data Requirement	• Quantity of outputs and inputs • Revenue/cost shares (or prices of outputs and inputs)	• Quantity of outputs and inputs	• Quantity of outputs and inputs • Revenue shares of outputs (when using production function)
Strength	• Specification of functional form is not required • Easy to communicate	• Low data requirement (only output and inputs quantities are required) • Specification of functional form is not required • Can use physical measures of capital as proxy for capital input	• Accounts for statistical noise • Able to conduct hypotheses test • Firms on the frontier are not assumed to be 100% efficient.
Weakness	• High data requirement • Do not account for statistical noise	• Results are sensitive to outliers and to the set of DMUs included in the study • Does not account for statistical noise • Inability to distinguish among 100% efficiency DMUs	• High computational requirements • requires the specification of functional form

DATA CONSTRUCTION

Airports typically charge separately for handling aircrafts and passengers. Therefore, the numbers of aircraft movements (ATMs) and passenger volume are two major aeronautical outputs of an airport. Some argue that ATMs and passenger volume may be correlated and thus ATMs are not independent. In practice, airlines could change the number of flights by adjusting load factors, seating arrangements, and the sizes of aircraft, making ATMs unnecessarily endogenous. As another airport output, air cargo services are handled directly by airlines or third-party logistics companies. In addition, airports only receive small amounts of usage fees for leasing space and terminals, cargo revenue covers only a small percentage of the total airport revenue, and it is thus not reported separately by most airports. As such, air cargo is not included as an individual output when measuring the gross efficiency index, but it is included as an explanatory variable in the second stage regression analysis.

Airports further rely on a number of non-aeronautical activities to generate additional revenues, such as duty-free shops, beverages, car parking and concessions. Such leasing and outsourcing activities offer flexibility to airport managers by allowing them to respond efficiently to market forces. Although non-aeronautical activities are different from traditional aeronautical services, their revenues have become increasingly important and account for somewhere between 30% and 70% of total revenues of most of our sampled airports in 2006. As discussed in Oum et al. (2006)

and Zhang et al. (2010), aeronautical and non-aeronautical activities are not separable, and their demands are closely related to each other. Any efficiency measure computed without including non-aeronautical service output would lead to serious bias against the airports that focus on increasing non-aeronautical revenue in order to reduce airport charges to airlines and passengers. Therefore, this study includes non-aeronautical revenue as the third airport output.[12]

Regarding airports, certain resources are used to provide the services stated above. First, labor is one of the most important inputs. In 2006, personnel expenses accounted for somewhere between 15% and 70% of total operating cost of the sampled airports. As most airports contract out part of their services, some employees are hired by outsourcing companies rather than airport operators. To avoid double counting, this study defines labor input as the full-time equivalent number of employees directly paid for by airport operators. Due to lack of consistent separate data on the outsourced services for the goods, services, and materials purchased directly by an airport, this study defines "soft cost input" to be other variable inputs other than labor input. The concept of soft cost input has been used in previous airport benchmarking studies including ATRS (2001-2011).

In reality, there may be hundreds (if not thousands) of items included in our soft cost inputs that an airport uses during a year. Unless quantities and cost shares of all of these items for all of the airports in the sample are available to the analysts, it is impossible to create an aggregate quantity index for soft cost inputs. Therefore, the method of deflating aggregate soft cost input dollar values by purchasing power parity (PPP) of the year is used. Further, this is divided by the cost of living index of the city in which the airport is located. This is the next best feasible method for creating an approximate quantity index of the soft cost input for the airports in the sample.

Due to various geographic locations, airports in northern regions may incur additional snow removal costs. These airports have extra expenses in hiring additional staff and purchasing snow-removal equipment and supplies. For some airports, snow removal costs could be significant, e.g., in 2006 snow removal cost was estimated to be $9.8 million for the New York JFK airport and over $10 million for the Denver airport. In order to create a fairer comparison, this study deducts snow removal costs from airport expenses.[13]

To address the price differences between the U.S. and Canada, this study uses PPP[14] to deflate non-aeronautical revenues. In order to deal with the price differentials of non-aeronautical revenue items across different cities within a country, the paper further applies the city-based Cost of Living Index (COLI)[15] to deflate non-aeronautical revenue to compute the quantity index of non-aeronautical revenue output.[16] Table 2 provides descriptive statistics for the airport inputs and outputs used in this study.

Table 2: Summary Statistics for Output and Input Variables

	Mean	Median	Maximum	Minimum	Std. Dev
No. Of Passenger	21,462,585	15,730,771	84,846,639	2,899,460	2,328,169
ATM (Air Transport Movements)	293,672	236,723	965,496	60,518	25,236
Non-Aeronautical Revenue Output[1]	88,944,551	63,268,716	288,188,161	13,237,866	8,131,930
No. of Employee	554	407	3,000	123	62
Soft-Cost Input[2]	71,637,907	50,521,745	249,734,305	9,708,149	8,061,183

[1] Deflated by cost of living index.

[2] Snow removal cost is deducted and deflated by cost of living index.

ESTIMATION RESULTS

Based on an identical airport sample, efficiency scores and airport rankings are estimated and compared across the three methods. In addition, as gross efficiency measurement is affected by a number of airport characteristics and may not reflect airports' managerial efficiencies, the paper estimates and compares airport residual efficiencies after removing factors beyond managerial controls.

Comparison of "Gross" Efficiency Results Across the Alternative Methods

Since it is not meaningful to compare actual values of the gross efficiency scores generated by each of the three methods, the efficiency scores generated by each method are normalized around the most efficient airport by setting the value for the most efficient airport at one. After that, airport rankings obtained from these three methods are compared based on their gross efficiency scores. Table 3 reports these efficiency rankings obtained from the gross efficiency scores calculated by each method, together with the mean ranking, mean efficiency, and standard deviations. Some airports have consistent gross rankings regardless of methodologies used, for example, ATL, CLT, RDU, STL, MIA, and MSY. It is found that the rankings in the top and bottom ranges of the gross efficiency scores are quite robust with respect to methodology. Meanwhile, the rankings of some other airports, especially the mid-ranked ones, are more sensitive to the methodology used. For instance, SAT and RNO are ranked between 20 and 30 places in gross VFP and SFA, while these airports are estimated to have 100% gross efficiency by the DEA method. These considerable differences might be explained by the impossibility of the DEA method to distinguish among a large number of 100% efficient firms.

Table 4 reports the Spearman's rank order correlation coefficients of gross efficiency estimates by the three methods. In general, the three sets of efficiency scores are highly correlated with each other. The correlation between VFP and SFA is the highest, implying that both methods yield rather similar (gross) efficiency rankings. Further, the sample is divided into three groups based on average efficiency scores: the top 15 airports (25% of the top-ranked airports), mid-ranked airports, and the bottom 15 airports (25% of the bottom-ranked airports), and their correlations compared again. The results reveal that the correlations for the mid-ranked airports are the lowest, especially between the DEA and SFA models, where it is 0.29 and not statistically significant.

Impact of Airport Specific Characteristics on Gross Efficiency Result

The gross efficiency scores derived in the previous section are affected by a number of airport characteristics, for example, airport output size, capacity constraint, level of commercial services, etc. As some of these factors are beyond an airport manager's control, the gross measure of efficiency scores are not necessarily good estimators for airports' managerial performances. Therefore, this section applies regression analysis to decompose gross efficiency scores estimating the impacts of airport characteristics on measured efficiency.

A log-linear OLS (Ordinal Least Squares) model is used to decompose gross VFPs. However, as gross DEA and SFA efficiency scores have an upper bound of 1.0, there might be a truncation bias if the OLS model is used. Thus, as has been done in many previous studies, a Tobit regression model (Tobin 1958) on DEA scores is used.

Based on previous airport efficiency studies, including the ATRS Global Airport Performance benchmarking report, the following variables are incorporated in the regression function as these may affect the gross efficiency scores.

Table 3: Comparative Gross Efficiency Rankings by the Alternative Methods

Airport Code	Airport Name	VFP	DEA	SFA	Mean Ranking	Std. Dev. (Ranking)	Mean Efficiency Score	Std. Dev. (Score)
ATL	Hartsfield-Jackson Atlanta International Airport	1	1	1	1	0	0.978	0.039
CLT	Charlotte Douglas International Airport	2	1	3	2	1	0.974	0.041
MSP	Minneapolis/St. Paul International Airport	3	1	2	2	1	0.953	0.041
RDU	Raleigh-Durham International Airport	4	1	4	3	1.7	0.945	0.047
YVR	Vancouver International Airport	5	1	5	3.7	2.3	0.926	0.07
YYC	Calgary International Airport	6	1	6	4.3	2.9	0.904	0.096
RIC	Richmond International Airport	7	1	9	5.7	4.2	0.897	0.102
ABQ	Albuquerque International Sunport	9	1	13	7.7	6.1	0.863	0.149
LGA	LaGuardia International Airport	15	1	11	9	7.2	0.845	0.182
TPA	Tampa International Airport	10	18	8	12	5.3	0.807	0.106
SDF	Louisville International-Standiford Field	8	14	17	13	4.6	0.848	0.106
MCO	Orlando International Airport	20	13	10	14.3	5.1	0.818	0.182
RNO	Reno/Tahoe International Airport	23	1	24	16	13	0.823	0.206
LAS	Las Vegas McCarran International Airport	16	26	7	16.3	9.5	0.759	0.133
MEM	Memphis International Airport	12	22	21	18.3	5.5	0.77	0.11
MKE	General Mitchell International Airport	11	19	25	18.3	7	0.781	0.104
SLC	Salt Lake City International Airport	17	23	16	18.7	3.8	0.764	0.126
BNA	Nashville International Airport	14	21	22	19	4.4	0.767	0.113
SAT	San Antonio International Airport	31	1	26	19.3	16.1	0.804	0.236
EWR	Newark Liberty International Airport	39	1	19	19.7	19	0.796	0.257
CVG	Cincinnati/Northern Kentucky International Airport	13	29	18	20	8.2	0.752	0.117
SNA	John Wayne Orange County Airport	21	15	28	21.3	6.5	0.798	0.172
YWG	Winnipeg International Airport	19	16	35	23.3	10.2	0.794	0.149
DEN	Denver International Airport	29	27	15	23.7	7.6	0.729	0.156
PHX	Phoenix Sky Harbor International Airport	27	31	14	24	8.9	0.728	0.152
PDX	Portland International Airport	18	32	23	24.3	7.1	0.738	0.125
IAH	Houston-Bush Intercontinental Airport	22	40	12	24.7	14.2	0.698	0.163
IND	Indianapolis International Airport	26	28	27	27	1	0.728	0.139
SEA	Seattle-Tacoma International Airport	24	38	20	27.3	9.5	0.698	0.158
JAX	Jacksonville International Airport	25	25	34	28	5.2	0.733	0.132
FLL	Fort Lauderdale Hollywood International Airport	34	24	31	29.7	5.1	0.717	0.17
IAD	Washington Dulles International Airport	32	33	32	32.3	0.6	0.704	0.163
YUL	Montréal-Pierre Elliott Trudeau International Airport	33	34	33	33.3	0.6	0.696	0.16
PBI	Palm Beach International Airport	37	20	44	33.7	12.3	0.717	0.171
YEG	Edmonton International Airport	30	30	43	34.3	7.5	0.704	0.134
DTW	Detroit Metropolitan Wayne County Airport	35	42	30	35.7	6	0.665	0.177
YOW	Ottawa International Airport	28	41	45	38	8.9	0.673	0.135
BOS	Boston Logan International Airport	42	36	38	38.7	3.1	0.653	0.186
DCA	Ronald Reagan Washington National Airport	36	45	36	39	5.2	0.639	0.184
SAN	San Diego International Airport	40	37	40	39	1.7	0.655	0.171
JFK	New York-John F. Kennedy International Airport	56	17	49	40.7	20.8	0.675	0.269
ORD	Chicago O'Hare International Airport	43	52	29	41.3	11.6	0.615	0.217
HNL	Honolulu International Airport	38	48	39	41.7	5.5	0.628	0.186
DFW	Dallas Fort Worth International Airport	49	44	37	43.3	6	0.622	0.208
OAK	Oakland International Airport	46	35	50	43.7	7.8	0.639	0.187
MDW	Chicago Midway Airport	48	39	48	45	5.2	0.628	0.188
CLE	Cleveland-Hopkins International Airport	41	49	47	45.7	4.2	0.612	0.186
SFO	San Francisco International Airport	51	47	41	46.3	5	0.599	0.211
MCI	Kansas City International Airport	47	43	51	47	4	0.614	0.183
YHZ	Halifax International Airport	44	46	56	48.7	6.4	0.592	0.163
LAX	Los Angeles International Airport	55	50	42	49	6.6	0.579	0.23
AUS	Austin Bergstrom Airport	45	51	52	49.3	3.8	0.589	0.185

(continued)

Table 3 continued

Airport Code	Airport Name	VFP	DEA	SFA	Mean Ranking	Std. Dev. (Ranking)	Mean Efficiency Score	Std. Dev. (Score)
PHL	Philadelphia International Airport	50	60	46	52	7.2	0.561	0.231
PIT	Pittsburgh International Airport	53	54	54	53.7	0.6	0.545	0.204
STL	St. Louis-Lambert International Airport	52	56	53	53.7	2.1	0.541	0.217
SMF	Sacramento International Airport	54	53	55	54	1	0.548	0.203
ONT	Ontario International Airport	57	58	58	57.7	0.6	0.509	0.209
ALB	Albany International Airport	58	55	61	58	3	0.506	0.188
SJC	Norman Y. Mineta San José International Airport	59	57	59	58.3	1.2	0.508	0.208
BWI	Baltimore Washington International Airport	60	59	57	58.7	1.5	0.51	0.223
MIA	Miami International Aiport	62	61	60	61	1	0.446	0.244
MSY	Louis Armstrong New Orleans International Airport	61	62	62	61.7	0.6	0.427	0.208

Table 4: Spearman's Rank Order Correlation Coefficients Among Airport Gross Efficiency Estimates

	All Sample		Top 15 airports		Mid-ranked airports		Bottom 15 airports	
	VFP	DEA	VFP	DEA	VFP	DEA	VFP	DEA
DEA	0.8338**	1	0.5145**	1	0.4154**	1	0.725**	1
SFA	0.9116**	0.8113**	0.8107**	0.3615	0.6727**	0.2913	0.7071**	0.6**

**correlation is statistically significantly different from zero at the 5% level, two-sided.

*correlation is statistically significantly different from zero at the 10% level, two-sided.

Variables Beyond Airports' Managerial Control

Congestion Delay. Many of the sampled airports suffer from runway and terminal congestion. Pathomsiri et al. (2008) found that the performance ranking of airports would be distorted in favor of congested airports because they have higher utilization of all inputs, while delayed flights are costly to airlines and passengers. In order to control the former effect, the study incorporates the percentage of non-weather delays as an indicator for congestion delay.

Airport Output Scale. Airports handling more outputs are expected to achieve higher operating efficiency, because the continuous flow of outputs helps airports to better utilize their employees and other inputs.

Average Aircraft Size. Large aircrafts carry more passengers and cargo at one time, which requires a larger number of operators and other facilities to provide land services. Thus, airports have to provide sufficient landside capacity for "peak" hours; however, this leads to a lower utilization and productivity in "off-peak" hours. On the other hand, airports that mostly handle large aircraft tend to have higher utilization of airside facilities.

Percentage of International Traffic. International traffic requires more airport services than domestic traffic. On the other hand, airports collect more revenues from international passengers. As a result, the impact of international traffic on airport efficiency depends on the counter-balancing effects of these two factors.

Percentage of Air Cargo. Providing cargo service may have a mixed impact on airport efficiency. While costs are lower to serve cargo traffic, airports may also lose a portion of non-aeronautical revenues that come with passenger traffic. Since the output index used to calculate gross productivity does not include cargo as a separate output, the study incorporates the percentage of cargo as a variable in the regression models in order to control for the effect of cargo on airport efficiency.

Percentage of Connecting Passengers. Hub airports usually have a significant number of connecting passengers. Connecting passengers require less service than do passengers on direct flights. Therefore, airports with a high proportion of connecting passengers are expected to have high productivity.

Hub Carrier Market Share. The dominance of a hub carrier at an airport may allow better coordination and cooperation between the carrier and the airport. Therefore, airports that are dominated by a hub carrier are expected to have higher efficiencies than airports with a large number of competing airlines.

Variable Within Airport's Managerial Control

Percentage of Non-Aeronautical Revenue. This indicator is used to present the business strategy of an airport. Commercial activities expand airport revenue; however, they also require additional resources. Therefore, it is necessary to examine the impact of non-aeronautical activities on airport efficiency.

Table 5 reports the second stage regression results for the three models.[17] All three results show consistently that airport congestion delay, percentage of cargo services, or hub carrier's market share does not have statistically significant impacts on an airport's operating efficiency.

Table 5: Regression Results on the Gross Efficiency Scores

	VFP OLS (log-log)		DEA Tobit (log-log)		SFA Tobit (log-log)	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**
Congestion Delay	0.012	0.07	0.128	0.5	-0.005	-0.14
Output Size	0.231**	3.46	0.207**	2.26	0.086**	5.94
Ave. Aircraft Size	-0.39**	-3.23	-0.197	-1.18	-0.080**	-3.08
% International	-0.021*	-1.71	-0.037**	-2.08	-0.006**	-2.22
% Cargo	-0.037	-1.19	-0.01	-0.23	-0.006	-0.93
% Non-Aeronautical Revenue	0.572**	4.22	0.615**	3.23	0.114**	3.91
% Connecting Passenger	0.027**	2.01	0.033*	1.72	0.005*	1.68
% Hub Carrier	0.003	0.05	-0.026	-0.29	-0.009	-0.65
Intercept	1.283	2.07	0.972	1.12	0.189	1.41
R^2	*0.55*		-		-	
Log-likelihood value	-		*-19.15*		*87.12*	

*The coefficient is significant at the 90% level.

**The coefficient is significant at the 95% level.

The output size variable has significant positive coefficients in all of the three regressions (VFA, DEA, and SFA). This means that the larger the output size, the higher the operating efficiency the airport is expected to achieve. This evidence does not translate into scale economies because the dependent variable in these regressions is only operating efficiency, not total efficiency. Given the quasi-fixed nature of airport capacity in the short run, this evidence may be interpreted as economies of utilization of the given capacity.

Average aircraft size has a statistically significant negative coefficient in the VFP and SFA regressions while not being significant in the DEA regression. This negative coefficient is surprising, and could be the result of more inputs required to service large aircraft.[18]

The statistically significant negative coefficient for the percentage of international (passenger) variables in all of the three models indicates that international traffic requires more resources to deal with customs, immigrations, and more stringent security.

The significant positive coefficient for the percentage of connecting passengers indicates that airports with high proportions of connecting passengers (hub airports) are expected to have high operating efficiency. This is probably because a connecting passenger at an airport is counted twice (deplanement and enplanement), and thus, requires fewer airport resources (not requiring check-in facilities, baggage areas, etc.).

As described above, the percentage of non-aeronautical revenue in total airport revenue is the only variable that can be largely chosen (controllable) by airport managers among the variables included in the second stage regression analysis. Consistent with many previous studies, including Oum et al. (2006, 2008) and Tovar and Martin-Cejas (2009), the percentage of non-aeronautical revenue has significant positive effects on operating efficiency of airports in all three regressions. Thus, an airport that derives a high percentage of its total revenue from non-aeronautical activities is expected to fare well in all three measures of operating efficiency.[19] This result implies that making more effort to increase non-aeronautical revenue beyond the current level of average efforts being expended by the North American airports would increase an airport's operating efficiency, and thus, should be encouraged.

Managerial Efficiency Results Based on the Alternative Methods

After removing the effects of airport characteristics beyond managerial control, residual (managerial) efficiencies[20] are estimated and airports are ranked by their managerial efficiencies. Similar to the gross efficiency estimates, the sample is divided into three groups: the top 15 airports, the bottom 15 airports, and the mid-ranked airports. The comparative residual efficiency rankings between the three alternative methodologies are reported in Table 6. To provide a clear picture of the residual efficiency rankings, Figures 1, 2, and 3 plot the results of the three alternative methods for the top 15, the bottom 15, and the mid-ranked airports. For the top 15 airports, except for BNA (Nashville), airport rankings are largely consistent across the three alternative methods. Most airports in this group have similar efficiency rankings regardless of the method of measurement used. The rankings for the bottom 15 airports are also similar across the three methods except for BOS (Boston) and PHL (Philadelphia). In contrast, significant variations exist in the rankings of mid-ranked airports, notably SEA (Seattle), EWR (Newark), and JFK (New York). Based on the average residual efficiency scores, Atlanta (ATL), Raleigh-Durham (RDU), Charlotte (CLT), Minneapolis-St. Paul (MSP), and Reno (RNO) are the top five most efficient airports in the sample of U.S. airports studied.

In general, the three sets of airport managerial/operational efficiencies are highly correlated with each other as indicated in the Spearman's rank order correlation coefficient reported in Table 7. Similar to the results in gross efficiency estimates, the ranking results between VFP and SFA are more consistent with each other. Because of many corner solutions in DEA measurement and the consequent existence of a large number of efficient DMUs (airports in this case), the managerial efficiency rankings based on DEA method are considerably different from those of the other two methods. The correlation between VFP and DEA for the mid-ranked airports is not even statistically significant.

Table 6: Comparative Airport Rankings by Residual (Managerial) Efficiency Scores

Airport	VFP	DEA	SFA	Mean Ranking	St. Dev. (Ranking)	Mean Efficiency Score	Std Dev (Score)
			Top 15 Ranked Airports				
ATL	3	1	3	2.3	1.2	1.146	0.109
RDU	2	5	4	3.7	1.5	1.101	0.122
RNO	9	2	1	4.0	4.4	1.030	0.134
CLT	1	7	6	4.7	3.2	1.081	0.819
PBI	7	3	5	5.0	2.0	1.029	0.109
BNA	5	12	2	6.3	5.1	1.013	0.102
MSP	4	9	7	6.7	2.5	1.035	0.853
JAX	6	13	8	9.0	3.6	0.966	2.082
LGA	11	4	13	9.3	4.7	0.973	0.106
SAT	12	10	9	10.3	1.5	0.928	0.111
TPA	8	14	10	10.7	3.1	0.945	0.111
SNA	10	16	11	12.3	3.2	0.905	1.701
MCO	13	8	18	13.0	5.0	0.927	0.117
MKE	15	17	12	14.7	2.5	0.871	0.118
FLL	16	15	15	15.3	0.6	0.880	2.531
			Middle Ranked Airports				
PDX	14	21	14	16.3	4.0	0.853	0.124
SAN	19	24	16	19.7	4.0	0.819	0.131
SLC	22	20	20	20.7	1.2	0.814	0.130
OAK	25	19	19	21.0	3.5	0.820	0.137
RIC	18	25	21	21.3	3.5	0.821	0.142
ABQ	23	18	23	21.3	2.9	0.828	3.377
SEA	17	35	17	23.0	10.4	0.802	2.565
HNL	20	27	22	23.0	3.6	0.811	0.151
EWR	38	6	28	24.0	16.4	0.868	0.150
IAD	27	22	26	25.0	2.6	0.794	0.152
LAS	21	30	25	25.3	4.5	0.791	0.152
MEM	30	23	29	27.3	3.8	0.781	0.154
MDW	32	28	27	29.0	2.6	0.765	0.157
DCA	26	38	24	29.3	7.6	0.751	0.161
IAH	24	37	30	30.3	6.5	0.760	0.162
JFK	45	11	36	30.7	17.6	0.794	0.164
IND	33	29	31	31.0	2.0	0.756	0.165
PHX	29	33	33	31.7	2.3	0.753	0.166
SMF	31	26	38	31.7	6.0	0.765	0.167
AUS	28	40	32	33.3	6.1	0.735	0.171

(continued)

Table 6 continued

Airport	VFP	DEA	SFA	Mean Ranking	St. Dev. (Ranking)	Mean Efficiency Score	Std Dev (Score)
			Middle Ranked Airports (continued)				
SDF	34	31	37	34.0	3.0	0.743	5.457
DEN	37	34	39	36.7	2.5	0.729	0.173
DTW	36	41	35	37.3	3.2	0.712	0.178
SFO	40	39	34	37.7	3.2	0.709	0.178
MCI	39	36	41	38.7	2.5	0.715	7.506
			Bottom 15 Ranked Airports				
BOS	41	32	43	38.7	5.9	0.721	0.181
CVG	35	43	40	39.3	4.0	0.702	0.187
CLE	43	44	42	43.0	1.0	0.678	0.188
SJC	42	45	45	44.0	1.7	0.671	0.183
ALB	44	42	50	45.3	4.2	0.669	0.185
PHL	46	54	44	48.0	5.3	0.618	3.856
DFW	53	46	47	48.7	3.8	0.630	0.196
STL	49	52	46	49.0	3.0	0.614	0.200
ONT	48	48	51	49.0	1.7	0.623	0.200
LAX	54	47	48	49.7	3.8	0.617	0.203
ORD	50	51	49	50.0	1.0	0.612	0.206
BWI	51	49	53	51.0	2.0	0.616	0.209
PIT	52	50	52	51.3	1.2	0.609	5.103
MSY	47	53	54	51.3	3.	0.594	3.070
MIA	55	55	55	55.0	0.0	0.506	0.625

Figure 1: Residual Ranking Comparison of Top 15 Airports

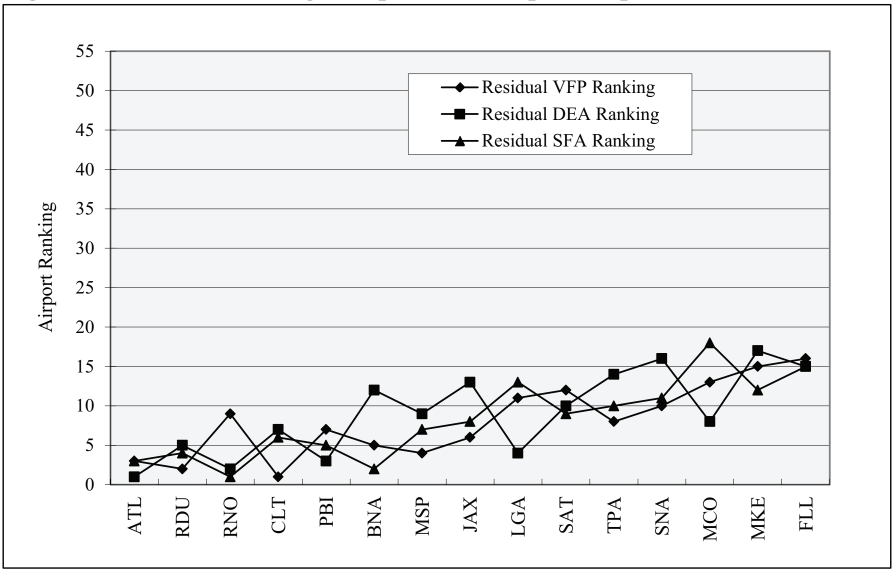

Figure 2: Residual Ranking Comparison of Bottom 15 Airports

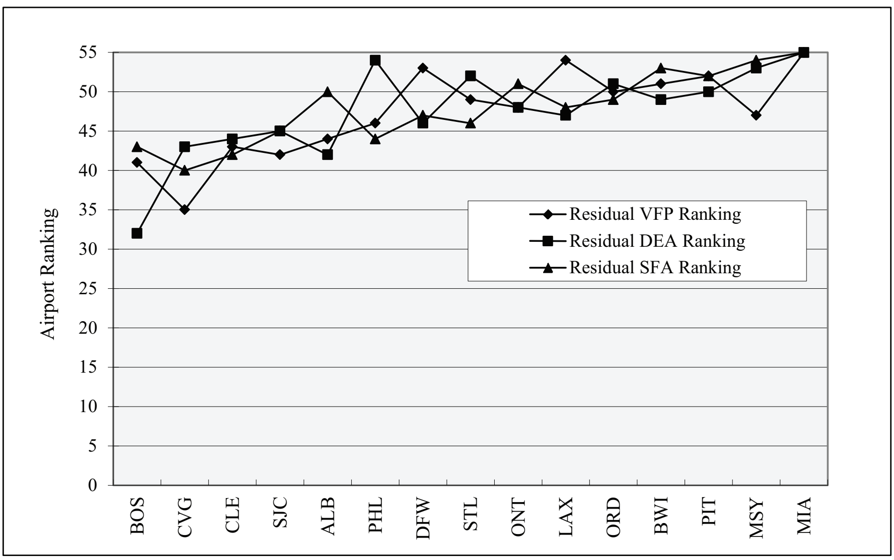

Figure 3: Residual Ranking Comparison of Mid-Ranked Airports

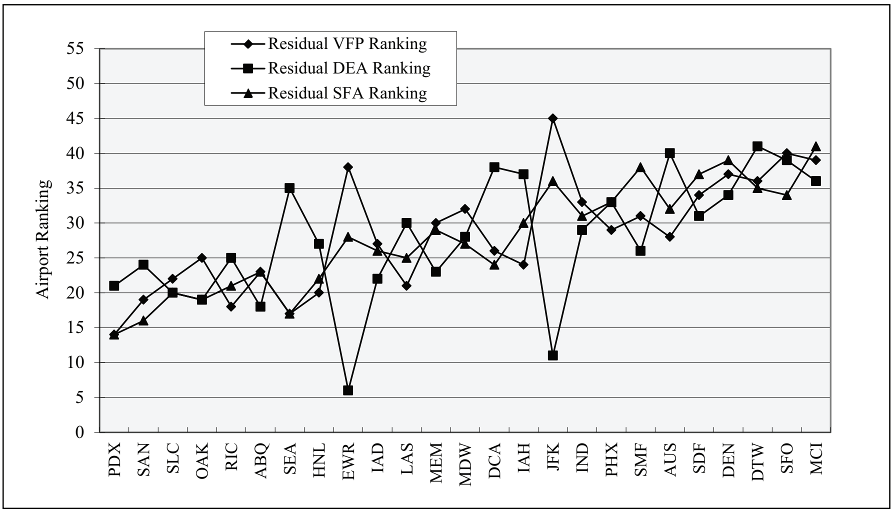

Table 7: Spearman's Rank Order Correlation Coefficients Among Residual Efficiency Estimates

	All sample		Top 15 airports		Mid-ranked airports		Bottom 15 airports	
	VFP	DEA	VFP	DEA	VFP	DEA	VFP	DEA
DEA	0.8468**	1	0.4643*	1	0.18	1	0.5821**	1
SFA	0.969**	0.8899**	0.7393**	0.55**	0.8577**	0.4154**	0.675**	0.5571**

*correlation is statistically significantly different from zero at the 10% level, two-sided.

**correlation is statistically significantly different from zero at the 5% level, two-sided.

CONCLUSION AND FURTHER RESEARCH NEED

This study reviews and compares airport operating efficiency indices measured by VFP (Variable Factor Productivity), DEA (Data Envelopment Analysis), and SFA (Stochastic (Production Frontier Analysis) methods, which have been used widely in past studies. Based on a sample of 62 major Canadian and US airports, this paper has compared the "gross" and managerial ("residual") operating efficiency scores and airport rankings estimated by each of these three alternative methods.

Both the gross efficiency and residual efficiency estimates by these three alternative methods are highly correlated. The airport efficiency rankings for both the top 15 and the bottom 15 airports are largely consistent across these three alternative methods, while significant differences exist in the mid-ranked airports. However, because of many corner solutions in DEA measurement and the consequent existence of a large number of efficient airports, the efficiency rankings based on the DEA method are considerably more different from those of the other two methods.

Given that the DEA application to the data has identified 12 efficient airports, each with gross DEA score of one (Table 3), it begs an important question whether or not there are truly significant differences in operating efficiencies among the top 10-15 airports, and if there are, how deep are the differences. This begs for further research of the top 10-15 airports (especially those 12 airports with gross DEA value of 1.0) based on micro-data.

Based on the average residual efficiency scores, Atlanta (ATL), Raleigh-Durham (RDU), Charlotte (CLT), Minneapolis-St. Paul (MSP), and Reno (RNO) show up as the top five most efficient airports in the U.S.

Endnotes

1. In the short run, airlines wishing to serve certain markets do not have much choice of airports, but in the end, airlines will consider efficient versus inefficient airports when they restructure their route networks.

2. The direct and/or indirect regulators such as aviation departments of cities and the FAA have various means to exert pressure on inefficient airports. Therefore, benchmarking of efficiency among peer airports provides at least indirect pressure on airport management to pay attention on efficiency.

3. To save space, this paper will not review the literature on airport productivity and efficiency in detail, please refer to Liebert and Niemeier (2010).

4. One should note that by excluding capital inputs and costs in the short-to-medium term efficiency analysis, this study aims to compare operating efficiencies that could be affected by airport managers in the short to medium term.

5. Since the CRS assumption may be violated for the airport industry, this problem is dealt with by including an output scale variable in the second stage regression analysis, which is discussed later.

6. Battese and Coelli (1992) define the concept of technical efficiency of a given firm as the ratio of its mean production to the corresponding production if the firm utilized its levels of inputs most efficiently.

7. This additional constraint represents a convexity constraint that ensures that an inefficient firm is only benchmarked against firms of a similar size.

8. On the other hand, one could argue that airport managers have more control over non-aeronautical activity volumes such as parking revenues, revenues from shops and restaurants, rental spaces, hotels, etc. This may be true only in the long run when capital investments on buildings and spaces can be adjusted, not necessarily so in the short to medium term for which the operating efficiency measures are based. Related to non-aeronautical revenue output, recent studies including Zhang et al. (2010), have discovered the increasing importance of external effects of increased aeronautical outputs airlines bring to an airport on the amount of non-aeronautical revenues the airport can generate. This implies that the aviation activity volumes are an increasing cause of the non-aeronautical revenue outputs.

9. The primary reason for using the SFA-production function instead of a cost function is the seemingly direct comparability of the three methodologies. Variable Factor Productivity (VFP) index is based on essentially the ratio of the output index and input index, and the DEA index directly relates outputs to inputs. Therefore, using a production function, which relates the output index directly to input quantities, serves the purpose of the study better. This also reduces our computational work.

10. The constant RTS allows cost shares to be used as aggregating weights for the inputs. Although the use of revenue shares of outputs as aggregating weights for outputs needs further assumptions, since the paper uses a single aggregate output index in all of the three methods, they are even on this dimension.

11. As pointed out by a referee, it is possible to detect outliers using methodologies such as Mahalanobis D2. There are two issues to confront. First of all, within the two-stage framework of analysis, without seeing results of the second stage analysis, it probably is hard to know what observations will be the outliers even if such methodologies as Mahalanobis D^2 are employed. Another issue is that it is expensive to researchers to lose several outlier airports' data points even if we are able to identify true outliers since it is expensive and time consuming to collect even one airport's data.

12. As a referee pointed out to us, airport revenue can be influenced by monopoly power. For example, an airport charging higher rates for parking may be influenced by the unavailability of close off-site parking options. Therefore, the airports with monopoly power may appear to be more productive than in reality.

13. The main reason why snow removal costs are removed from the total soft cost rather than including it in the second stage regression analysis is that for many airports, snow removal costs are zero. As such, this poses a problem in logarithmic transformation of the data unless some sort of transformation function such as Box-Cox form is used, which tends to complicate the analysis unnecessarily.

14. The Purchasing Power Parity (PPP) uses the long-term equilibrium exchange rate of two currencies to equalize their purchasing power. PPP equalizes the purchasing power of different currencies in their home countries for a given basket of goods.

15. The Cost of Living Index (COLI) is a composition index to measure the relative price level for consumer goods and services in areas for a mid-management standard of living. The overall index (100%) is composed of grocery items (13%), housing (29%), utilities (10%), transportation (10%), health care (4%), and miscellaneous goods and services (35%).

16. In the absence of COLI, city-based CPI is used to adjust Canadian airports. The COLI and CPI indices are linked with the US-Canada PPP exchange rate in 2006: 1US$=1.245CA$.

17. A variance inflation factor (*VIF*) diagnostic test was conducted after the OLS regression in order to see if there are significant multicollinearity problems among our explanatory variables. The test reveals there is no concern of multicollinearity problem. *Output size* and *percentage of International Traffic* have the highest *VIF* value of 2.18 and 2.04, respectively. As a rule of thumb, *VIF* values of considerably less than 10 do not raise concern in multicollinearity.

18. This negative coefficient for "aircraft size" in the second stage regression on the Canada/US airport data has been a bother for the last 10 years of the ATRS benchmarking work, especially because similar second stage regressions on European and Asian airport data show positive signs. However, this has been a consistent result over the last 10 years or so (even if each year's cross sectional data or a panel data of cross-section and time-series data are used). Some senior airport managers argue that the coefficient could be positive or negative. The authors would welcome further comments and/or research results on this issue.

19. A referee posed an interesting question on non-aeronautical revenue in the context of this paper's model, which excludes capital input (due to measurement problems) and focuses on operating efficiency measurement. The referee's point is that airport (a) with a lot of parking would be favored in our study as compared with airport (b) without any parking lots. While

this is a good counter example, the results on non-aeronautical revenue show that airport (a) should, in fact, be rated higher than airport (b). Airport (b) is not making a reasonable effort to increase non-aeronautical revenue, a part of which is parking revenue.

20. Since non-aeronautical revenue is controlled by airport managers, its effect is not deducted from "gross" scores when the residual efficiency scores are computed using the second stage regression results.

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Modeling Fatigue-Induced Collision Relative Risk: Implications of Service Hours and Fatigue Management Policies on Transit Bus Operators in Florida

by Enock Mtoi, Ren Moses, and Thobias Sando

This research explores the association between fatigue-induced crash risk, transit operator hours of service and fatigue management policies in the state of Florida. Data used in this study include incident data archived by transit agencies and bus driver schedules. The results show a decreasing trend of collision risks when drivers start their schedules late morning or afternoon compared with early morning. The effect of time on task shows increasing collision risk as drivers drive long hours without enough off duty periods.

INTRODUCTION

Driver fatigue has been identified as a high-priority commercial vehicle safety issue by the Federal Motor Carrier Safety Administration (FMCSA), the commercial motor vehicle industry, highway safety advocates, researchers, and the public (Barr et al. 2005). Different sources reported that driver fatigue and fatigue-related accidents are affected by a variety of variables, such as time of day effect due to circadian rhythm, sleep debt, monotonous driving environments, length of driving, weather conditions, use of alcohol and drugs, heat, vibration, and noise (Wyle et al. 1996). Agencies such as the Florida Department of Transportation (FDOT) that deal with regulating transit systems have established rules that limit operator duty periods to reduce fatigue. Although there are many reasons why managing service hours is a challenging task, the most perplexing is the inconsistency in research findings concerning the effect of driving schedules on driver performance and safety (Park et al. 2005). Operating rules are created to promote safe, efficient, timely, and customer-oriented transit operations. Most states have adopted intrastate regulations that are identical or very similar to the federal hours-of-service regulations. Table 1 shows differences between federal and Florida hours of service regulations. It indicates that Florida has a higher daily driving limit (12 hours compared with 10 and 11 hours for interstate carriers carrying passengers and commercial motor vehicles). The 16-hour on-duty limit in Florida is higher than the 15-hour limit for interstate passenger-carrying commercial motor vehicles' drivers.

FDOT's Bus Transit Draft Rule 14-90.006 states that a driver shall not be permitted or required to drive more than 12 hours in any one 24-hour period or drive after having been on duty for 16 hours in any one 24-hour period (Florida Administrative Register and Administrative Code 2008). The rule allows the 12 hours of driving time to be spread out provided they do not exceed 16 hours of on-duty time in any one 24-hour period. For example, in the worst case scenario, a driver might be on duty driving for eight hours and then take four hours break and return to on duty status for an additional eight hours (i.e., four hours driving and four hours non-driving). This would be considered as a maximum driving time of 12 hours and 16 hours on duty time in a 24-hour period, although the driver may not have had any rest for 20 hours. Rule 14-90.006 further states that a driver shall not be permitted to drive until the requirement of a minimum eight consecutive hours of off-duty time has been fulfilled (Florida Administrative Register and Administrative Code 2008).

Table 1: Hours of Service Rules

Federal regulation for property-carrying CMV drivers	Federal regulation for interstate passenger-carrying CMV drivers	Florida Regulation for bus transit (Rule 14-90)
11-Hour Driving Limit May drive a maximum of 11 hours after 10 consecutive hours off duty.	**10-Hour Driving Limit** May drive a maximum of 10 hours after 8 consecutive hours off duty.	**12-hour driving limit** a driver shall not be permitted or required to drive more than 12-hours in any one 24-hour period
14-Hour On-Duty Limit May not drive beyond the 14th consecutive hour after coming on duty, following 10 consecutive hours off duty. Off-duty time does not extend the 14-hour period.	**15-Hour On-Duty Limit** May not drive after having been on duty for 15 hours, following 8 consecutive hours off duty. Off-duty time is not included in the 15-hour period.	**16-Hour On-Duty Limit** May not drive after having been on duty for 16 hours, in any one 24-hour period. Off-duty time is not included in the 15-hour period.
60/70-Hour On-Duty Limit May not drive after 60/70 hours on duty in 7/8 consecutive days. A driver may restart a 7/8 consecutive day period after taking 34 or more consecutive hours off duty.	**60/70-Hour On-Duty Limit** May not drive after 60/70 hours on duty in 7/8 consecutive days.	**72-Hour On-Duty Limit** A driver who has reached the maximum 72 hours of on duty time during the seven consecutive days shall be required to have a minimum of 24 consecutive hours off duty prior to returning to on duty status.

Source: Federal Motor Carrier Safety Administration (2010)

Notably, the minimum eight consecutive hours of off-duty time stipulated in Rule 14-90.006 is not the net resting time. Part of the eight hours off-duty time may be used by drivers for activities such as traveling back and forth from work to home and running personal errands before and/or sleeping. Regarding the split schedule, it is presumed that operators would use the break time for resting to rejuvenate their bodies before assuming a subsequent shift. However, operators have been observed to use the break time for activities such as running personal errands instead of resting.

The preponderance of scientific literature strongly shows that long hours of work lead to fatigue that can degrade performance, alertness, and concentration, which increase safety risk. Several studies on the influence of operator schedule on accident occurrence have been conducted for the aviation, rail, and trucking industries (McCart et al. 2000, Williamson et al. 1995, Coplen and Sussman 2000). The search of literature did not reveal similar research efforts for bus operators despite a concern that bus operators' spread-hour schedules can lead to fatigue and hence increase the chance of crash occurrence. A thorough understanding of the correlation between transit accident occurrence and long duty hours caused by split schedules, together with the minimum eight consecutive hours of off-duty time, is crucial in setting transit operating rules.

The objective of this study is to analyze operator hours-of-duty policies in Florida and determine if there are safety impacts that may prompt changes to these policies. The study uses incident reports and operator schedule data archived by transit agencies to determine the relationship between crash involvement and operator schedules. Factors of interest in this study, as found in the existing hours of service policies, are the influence of shift pattern (start and end time), schedule pattern (split or straight time schedule), time spent on driving, and time off duty on fatigue and safety.

LITERATURE REVIEW

The concepts of "fatigue," "sleepiness," and "drowsiness" are sometimes used interchangeably. Sleepiness can be defined as the neurobiological need to sleep resulting from physiological wake and sleep drives (Johns 2000). Fatigue has, from the beginning, been associated with physical labor, or, in modern terms, task performance. Although the causes of fatigue and sleepiness may be different, their effects are very much the same, namely a decrease in mental and physical performance capacity.

It is comprehensible from everyday experience that fatigue has different causes; the most common is intensity and duration of physical work. To maintain health and efficiency, the recuperative processes must cancel out accumulated fatigue. Recuperation takes place not only during night-time sleep, but free periods during the day, and all kinds of pauses during work, also make their contributions.

Various studies have been conducted to develop relationships between fatigue and performance decreases in different industries. Particular significance is attached to studies of fatigue in traffic, because it is reasonable to suppose that fatigue plays an important part in mistakes and crashes. For the driver, the main effect of fatigue is progressive withdrawal of attention from road and traffic conditions leading to impaired performance behind the wheel. Fatigue influences driving behavior in various ways such as slower reaction time, reduced vigilance, unsafe car following behavior, speed choice, and reduced information processing. Several authors have shown indisputably that about four hours of continuous driving is enough to bring on a distinct reduction in the level of alertness, and thereby increase the risk of accidents (Feyer and Williamson 1995; Williamson et al. 1995; Knipling and Wang 1994). Fatigue and sleep are causal factors in thousands of crashes, injuries and fatalities annually (Knipling and Wang 1994). At the 1995 National Truck and Bus Safety Summit, driver fatigue was identified as the leading safety issue in the industry (U. S. Department of Transportation 1998) and the National Transportation Safety Board (NTSB) estimated 31% of all truck-driver fatalities and 58% of all single-truck crashes were fatigue related (Schultz 1998).

In an effort to identify factors affecting long-haul truck drivers' performance, McCart et al. (2000) performed face-to-face interviews with 593 long-distance truck drivers at rest areas and inspection points. They found six factors influence drivers falling asleep at the wheel. They are greater daytime sleepiness; more arduous schedules with more hours of work and fewer hours off-duty; older, more experienced drivers; short, poorer sleep on road; symptoms of sleep disorder; and greater tendency toward nighttime drowsy driving. The study further suggested that limiting drivers' work hours would enable them to get adequate sleep to reduce sleep-related crashes.

Using a different technique, Williamson et al. (1995) carried out a controlled experiment whereby they examined 27 professional truck drivers who completed a 12-hour, 900 kilometer trip under three different settings – a relay trip, a working-hour regulated one-way single trip, and a one-way (flexible) trip with no work-hour constraints. The results of the study indicated no difference in fatigue for the three different experimental settings. However, the study suggested that fatigue patterns were more related to pre-trip fatigue levels.

The review of literature thus far indicates that most studies' focus is more on other modes of transportation than on bus transit. Very few studies have examined the influence of fatigue specifically on city bus drivers. Santos et al. (2004) evaluated daytime and nighttime sleep, as well as daytime and nighttime drowsiness of professional shift-working bus drivers in Brazil. The study revealed that the sleep time of shift-working bus drivers was shorter and more fragmented when it occurred during the day than at night. Howarth (2002) investigated differences in self-reported sleep length and aspects of fatigue for a sample of bus transit operators in the northeastern United States who were working split- and straight-shift schedules. The study used questionnaires, which were distributed to 149 bus operators in Hartford, Connecticut. The results demonstrated expected relationships between sleep length and before/after-work measures of fatigue, whereby fatigue levels increased with decreasing sleep length.

It is important to recognize that the operational characteristics of city buses differ from those of other modes of mass transportation and trucking. Feyer and Williamson (1995) pointed out that although fatigue is a problem for coach drivers, it is not of the same importance for truck drivers. They argue that operationally, bus drivers are not as free as truck drivers to take rest on a need basis. Unlike trucks for example, bus routes are scheduled during peak hours because that is the time when buses get more riders. Also, unlike truck drivers, bus drivers have less flexibility in choosing their schedules based on what time of the day they feel more energetic to perform a task. City buses use mostly city streets while trucks use mostly highways. Buses stop more frequently than trucks. In addition to driving, bus operators in most agencies perform other tasks such as collecting fares and validating identity cards.

In order to reduce fatigue and fatigue-related accidents, management of driver hours-of-service for bus transit operators has been a continual safety challenge. One study found that the principal factor associated with decline in driver performance was time of day (Wyle et al. 1996). Furthermore, the study found that the number of driving hours and the cumulative number of days driving were not strong or consistent predictors of decline in driver performance. This study therefore examines operator hours-of-duty policies in Florida and determines if there are safety impacts that may prompt changes to these policies.

RESEARCH APPROACH

Data Collection

Data from four Florida transit agencies were acquired. Until 2009, there were 35 fixed-route transit systems operating in Florida. Data collected for this study were from 2007 to 2009. Due to difficulties in acquiring the data, and the requirements to deliver results on time, the research team categorized the agencies into two. Agencies operating a fleet of less than 200 buses were grouped as small size agencies and those operating a fleet of more than 200 buses were categorized as large size agencies. Appendix A shows that two large and two small agencies were selected for the study. The selection was based on agency willingness to provide the data. Jacksonville Transit Authority (JTA) and Lynx (the transit agency in Orlando) are the large size agencies while StarMetro and Regional Transit System (RTS) in Tallahassee and Gainesville, respectively, are the small size agencies. These agencies require bus operators to report all incidents including collisions with other vehicles and fixed objects.

From the incidents' databases of these agencies, data on bus crashes and operator schedules were extracted. The crash reports were then reviewed to identify bus crashes with other vehicles, bicycles, pedestrians, or fixed objects. Further examination was done to eliminate any preventable accident that was perceived as having been caused by factors other than fatigue. Pertinent collision attributes such as operator information, time of crash, date of crash, and type of crash were collected to enable additional analysis.

Model Formulation and Variable Design

A regression model is formulated to relate crashes to fatigue and other variables. In this model, the response variable takes two distinct values: Y = 1 if a crash occurred and Y = 0 if a crash did not occur. Because the responses are binary, the most common techniques to analyze them are logistic and probit regressions and they have been used in many crash studies (Hours et al. 2010, Robertson and Vanlaar 2008, Schiff et al. 2008). Because both models give similar results, the choice between which to use depends upon assumptions regarding the distribution of the responses. In this paper it is assumed that the responses follow logistic distribution leading to the choice of logistic regression with crashes as the dependent variable. The data collected from the agencies showed that there are two types of schedules; split- and straight-runs. A split-run schedule is where a person's normal work day is split into two or more segments while in a straight-run schedule, each operator has its own set of continuous work hours that do not change. The data also showed that there are three different work-starting times for drivers: early morning, late morning, and afternoon. Therefore, the variables were categorized by schedule types and work starting times. The predictors of relative collision risk are schedule types (split = SPL or straight = CON), time on task (TOT), off duty hours (OFF), and start time (ST). Appendix B shows descriptions of these predictors. The model does not include driver and vehicle characteristics. Although important, for privacy and personnel policy reasons, the agencies could not provide them.

Unlike ordinary linear regression, which can be solved explicitly, logistic regression equations are solved iteratively until a solution is reached (Hosmer 2000). The logistic regression model is:

$$(1)\quad \pi(x) = \Pr(Y = 1|X_i) = \frac{e^{[g(X_i,\beta)]}}{1 + e^{[g(X_i,\beta)]}}$$

Where, Y is a response variable representing crash occurrence (Y = 1) or nonoccurrence (Y = 0) for an individual driver *i*. X_i is a multivariate attribute vector for schedule characteristics of this driver, some arbitrary function of X_i, β a parameter vector, and $\pi(x)$ the probability that a crash occurs. Taking the logarithm of Eq. (1) and solving gives,

$$(2)\quad \boldsymbol{g}(x) = ln\left[\frac{\Pr(Y = 1|X_i)}{1 - \Pr(Y = 1|X_i)}\right] = ln\left[\frac{\Pr(Y = 1|X_i)}{\Pr(Y = 0|X_i)}\right] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_i x_i$$

From this equation, the coefficients represent changes in the log odds of the responses per unit changes in the predictors. Therefore, to predict the relative collision risk of each driver, exponentials are applied to each log odd. That is, if the log odd is *m*, the corresponding relative collision risk would be e^m.

Descriptive Statistics of Operator Schedules

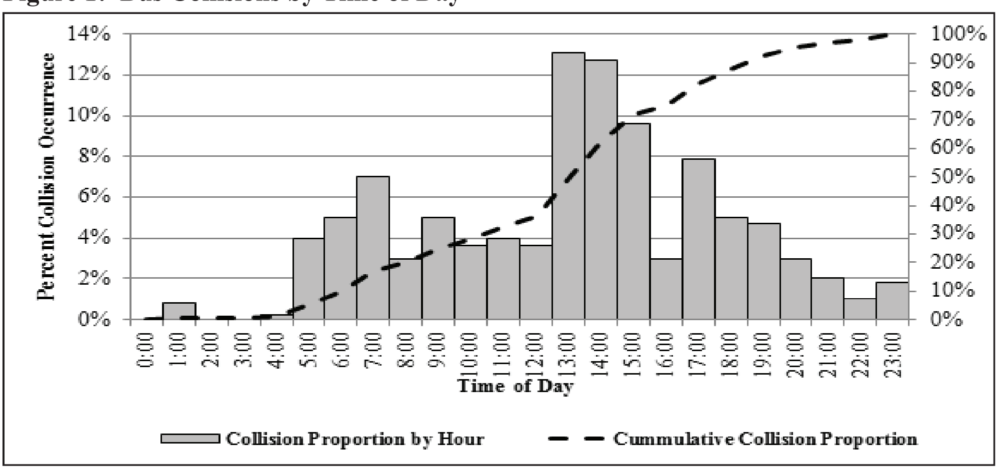
A total of 222 collisions were examined and descriptive statistics calculated. These statistics are in Table 2, and show a combined mean driving time of 49.8 hours for driving periods containing no split runs, with a 95% confidence interval of 48.7 hours to 50.9 hours. For operator weekly driving times containing split-run intervals, the combined mean driving time is 53.7 hours with a 95% confidence interval of 52.3 hours to 55.0 hours was calculated. The 95% confidence interval for the combined mean daily driving time for operators involved in collisions was also calculated. The statistics show a combined mean driving time is 9.8 hours for straight runs with a 95% confidence interval of 8.8 hours to 11.5 hours. For operator daily driving times containing split runs, the combined mean driving time is 11 hours with a 95% confidence interval of 10.2 hours to 11.9 hours.

The distribution of collisions by time of day is depicted in Figure 1. The smallest proportion of collisions occurred between midnight and 4:00 a.m., a reflection of both reduced routes and exposure late at night. It was also observed that collisions happened more often between 1:00 p.m. and 7:00 p.m. (56%) when traffic volumes are high with the largest proportion occurring between 1:00 p.m. and 3:00 p.m. (26%).

Table 2: Average Driving Hours of Operators Involved in Collisions and All Operators

Location	Average		Std. Deviation		Minimum		Maximum	
	Involved	All Drivers	Involved	All Drivers	Involved	All Drivers	Involved	All Drivers
Weekly average driving hours without split runs								
Gainesville	49.22	40.24	7.36	2.70	35.75	32.10	68.55	60.50
Jacksonville	49.94	46.39	7.58	6.99	36.77	32.60	70.00	64.22
Orlando	50.02	43.90	7.54	9.09	31.25	6.25	68.68	65.02
Tallahassee	49.71	41.26	10.71	3.71	16.90	27.00	70.00	56.00
Combined	49.81	43.52	8.64	7.50	16.90	6.25	70.00	65.02
Weekly average driving hours with split runs								
Gainesville	50.43	42.26	7.54	3.71	35.75	32.10	69.88	60.50
Jacksonville	54.34	51.79	8.46	10.90	39.95	32.60	71.56	85.67
Orlando	54.62	47.89	9.66	12.62	31.25	6.25	83.45	80.22
Tallahassee	53.35	46.73	11.82	9.41	30.50	27.00	81.35	70.50
Combined	53.67	47.65	9.85	11.06	30.50	6.25	81.35	85.67
Daily average driving hours without split runs								
Gainesville	9.85	8.34	1.55	0.82	7.10	6.67	14.10	10.21
Jacksonville	9.13	8.70	1.03	0.96	5.18	7.50	12.10	12.84
Orlando	10.84	8.70	1.50	1.54	8.00	2.87	14.40	11.75
Tallahassee	9.94	8.26	2.14	0.88	3.38	6.40	16.27	10.00
Combined	9.83	8.58	1.72	1.23	3.38	2.87	16.27	12.84
Daily average driving hours with split runs								
Gainesville	10.46	9.37	1.77	1.69	7.10	7.84	14.10	14.91
Jacksonville	10.89	9.73	3.08	1.87	7.88	7.50	21.65	14.55
Orlando	12.01	10.09	2.04	3.12	8.00	2.87	17.28	22.90
Tallahassee	10.67	9.36	2.37	1.95	6.10	6.40	18.94	15.30
Combined	11.01	9.77	2.58	2.49	6.10	2.87	21.65	22.90

Figure 1: Bus Collisions by Time of Day



Inferential Statistics to Compare Driving Hours

A one-tailed, two-sample *t*-test was used to determine whether the population of operators involved in collisions predominantly work longer hours or if driving schedules with split runs played a role in collision occurrences compared with the overall population sampled with similar schedules. The *t*-test statistics for weekly driving hours without splits and with splits are summarized in Table 3. The statistics show that, on average, drivers who were involved in collisions drove more than six hours more per week than that of the general population of drivers. The results of the one-tailed, two-sample *t*-test revealed that a significant difference exists for all four agencies and for the combined data. It is therefore statistically evident that operators who are involved in collisions drive more hours compared with the population of all drivers. Additionally, the one-tailed, two-sample *t*-test was performed to examine if the population of operators involved in collisions worked longer hours or if daily scheduled split runs influenced the likelihood of collisions compared with the general population of operators. The one-tailed, two-sample *t*-test statistics for daily driving hours are in Table 3. The results show a statistically significant difference between the operators

Table 3: Test Statistics –Daily and Weekly Driving Hours

Test Results - Collisions for driving periods without split runs						
Location	**Sample size**		**Mean Hours**		T-Value	P-Value
	Involved	All drivers	Involved	All drivers		
Gainesville	23	132	49.22	40.24	-5.78	0.00
Jacksonville	80	172	49.94	46.39	-3.55	0.00
Orlando	47	296	50.02	43.90	-5.02	0.00
Tallahassee	72	77	49.70	41.26	-6.34	0.00
Combined	222	677	49.81	43.52	-9.71	0.00
Test Results - Collisions for driving periods with split runs						
Location	**N Sample size**		**Mean Hours**		T-Value	P-Value
	Involved	All drivers	Involved	All drivers		
Gainesville	23	132	50.43	42.26	-5.09	0.00
Jacksonville	80	172	54.34	51.80	-2.02	0.022
Orlando	47	296	54.62	47.90	-4.24	0.00
Tallahassee	72	77	53.30	46.73	-3.76	0.00
Combined	222	677	53.67	47.70	-7.66	0.00

Test Results – Collisions for daily driving periods without split runs						
Gainesville	23	132	9.85	8.34	-4.59	0.00
Jacksonville	80	172	9.13	8.70	-3.13	0.001
Orlando	47	296	10.84	8.70	-9.02	0.00
Tallahassee	72	77	9.94	8.26	-6.17	0.00
Combined	222	677	9.83	8.58	-9.99	0.00
Test Results – Collisions for daily driving periods with split runs						
Gainesville	23	132	10.46	9.37	-2.73	0.011
Jacksonville	80	172	10.89	9.73	-3.10	0.003
Orlando	47	296	12.01	10.09	-5.53	0.00
Tallahassee	72	77	10.67	9.36	-3.68	0.00
Combined	222	677	11.01	9.77	-6.24	0.00

driving longer hours per day, or with split runs during the day, were more likely to be involved in a preventable collision.

Selection of Variables for the Model

Four variables were selected for inclusion in the model (i.e., start time, hours on a task, off-duty hours, and schedule type) because the study focuses on hours of service policies for transit bus operators in the state of Florida. Impacts of schedule type, off-duty hours, and hours spent on driving were presumed to be significant contributors to fatigue.

Table 4 summarizes likelihood ratio test for the variable. The Chi-square value of the start time is 33.766 with two degrees of freedom. The start time probability value of 0.000 indicates high significance as do the values for hours on task and off-duty hours. However, the probability value of 0.72 for schedule type indicates that this variable is not significant at the 0.05 probability level. Using a forward elimination method, schedule type was omitted and the model re-estimated. The remaining variables were all statistically significant after the second attempt.

Table 4: Likelihood Ratio Test for Each Variable

	First attempt			**Second attempt**		
Variable	Chi-square	DF	*p*-value	Chi-square	DF	P-value
Start Time (ST)	33.766	2	0.000	33.766	2	0.000
Hours on Task(TOT)	49.670	3	0.000	49.670	3	0.000
Off Duty Hours(OFF)	43.444	3	0.000	48.524	3	0.000
Schedule Type(CON, SPL)	5.234	1	0.72	Omitted	Omitted	Omitted
Overall Variables	132.117	9	0.000	131.960	8	0.000

Note: CON means continuous run; SPL refers to split run

Discussion of the Model

The accident risk of each variable was checked first by using its odd ratio. In keeping with the views in other safety studies (Hauer 2004), the discussion of each parameter is conducted using a null hypothesis test of significance; probability level of 0.05 is used to screen variables and identify those of particular interest. Table 5 shows the coefficient for each variable. The last column quantifies the size of the effects on collision odds relative to other variables. The results show that drivers starting work in the morning between 3:00 a.m. and 7:00 a.m. had higher collision odds (2.017) compared with drivers starting between 7:00 a.m. and 11:00 a.m. (1.262), and those starting between 11:00 a.m. and 3:00 p.m. (0.943). This might be due to the fact that work start times between 3:00 a.m. and 7:00 a.m. interfere with circadian low points which occur from 2:00 a.m. to 6:00 a.m. (Howarth 2002). Comparatively, based on the collision odds, the collision risk for drivers driving more than 16 hours within a 24-hour period (6.462) is higher than that of drivers driving less than eight hours (1.400), or driving between eight and 12 hours (1.406), and 13-16 hours (1.565). This is expected because fatigue and weariness increase with increases in exposure on the job. The importance of having enough off-duty time to sleep and release accumulated fatigue is shown by the collision odds for different off-duty hours. Drivers with less than eight hours off duty have higher collision odds (4.323), compared with those who are off duty eight to 16 (2.226) and more than 16 hours (1.822). These results suggest that there is a need for transit managers to design schedules with optimal balance between time on task and off-duty periods for safer operations.

Table 5: Parameter Estimates for Variables and Interaction Terms in the Model Equation

Variables		Coefficient	S.E	P-value	Collision Odds
Start Time	ST1	0.702	0.190	0.000	2.017
	ST2	0.232	0.203	0.252	1.262
	ST3	0.058	0.204	0.774	0.943
Hours on Task	TOT1	0.337	0.484	0.486	1.400
	TOT2	0.341	0.420	0.417	1.406
	TOT3	0.448	1.055	0.671	1.565
	TOT4	1.866	0.597	0.002	6.462
Off-duty Hours	OFF1	1.464	0.374	0.000	4.323
	OFF2	0.800	0.367	0.020	2.226
	OFF3	0.146	0.515	0.776	1.158
	OFF4	0.600	0.458	0.019	1.822
	Constant	-3.562	0.277	0.000	0.028
Interaction Terms		**Coefficient**	**S.E.**	**P-value**	**Collision Odds**
ST1 by CON		0.721	0.469	0.124	2.056
ST1 by SPL		0.862	0.336	0.010	2.367
ST# by SPL		0.725	0.294	0.014	2.064
ST4 by SPL		0.768	0.319	0.016	2.156
TOT2 by ST4		1.682	0.639	0.008	5.376
TOT4 by STe		3.222	1.002	0.001	25.087
OFF1 by ST1		2.306	0.839	0.006	10.035
OFF1 by ST4		1.276	1.071	0.233	3.584
OFF2 by ST1		1.756	0.643	0.006	5.789
OFF2 by ST4		0.971	0.745	0.193	2.641
OFF4 by ST1		1.518	0.771	0.049	4.561

Note: ST1 = 3:00 a.m to 7:00 a.m; ST2 = 7:00 a.m to11:00 a.m; ST3 = 11:00 a.m to 3:00 p.m; ST4 = later than 3.00 p.m;
TOT1 = Less than 8 hours; TOT2 = 8 to 12 hours; TOT3 = 13 to 16 hours; TOT4 = More than 16 hours;
OFF1 = Less than 8 hours; OFF2 = 8 to 12 hours; OFF3 = 13 to 16 hours; OFF4 = More than 16 hours;

Model Interaction Terms

The interactions among the variables were also examined to identify the effects of schedules with multiple characteristics. The analysis of variable interactions enables the identification of desirable balances between schedule characteristics. Two-, three-, and four-way interactions were performed and it was noted that three- and four-way interactions were statistically insignificant; therefore only two-way interactions were retained in the model. The results of this test are summarized in Table 5.

The interpretation of the interaction terms can be well understood by comparing the odd ratios (OR). For instance, among the drivers starting their schedules at 3:00 a.m. to 7:00 a.m. (ST1), a relative collision risk of drivers who work split runs (SPL) versus those who work straight runs (CON) is. This gives an estimated odds ratio of 2.367, i.e., ($e^{0.862}$). Therefore, among the drivers with work start time of 3:00 a.m. to 7:00 a.m., those who work split runs have higher collision odds (2.367) than (1) those working split-runs but starting work between 11:00 a.m. to 3:00 p.m. (2.064), and (2) others working split runs and starting later than 3:00 p.m. (2.156). Drivers starting work between 1:00 a.m. to 3:00 p.m. and working more than 16 hours a day, have much higher collision odds (25.087) compared with those who start work later than 3:00 p.m. and work eight to 12 hours a day (5.376). The effects of the interaction between off-duty hours and work start times indicate higher collision odds (10.035) for drivers who have been off duty less than eight hours compared with those who have been off duty more than eight hours off and starting work between 3:00 a.m. to 7:00 a.m. For transit managers and fatigue management policy makers, these results suggest that, if in a particular day, drivers finish their shifts late at night, the next shift should start late afternoon to allow enough time to release fatigue. Likewise, the number of working hours between shifts should be balanced to avoid long working hours, which is one of the main causes of fatigue. Shift rotations among drivers could be one of the best practices while maintaining efficient transit operations.

CONCLUSIONS AND RECOMMENDATIONS

This research explored the association between relative crash risk and existing transit operator hours of service policies in the state of Florida. Descriptive and logistic regression was used in the analysis. The logistic regression revealed a decreasing trend of collision risks when drivers start their schedules late morning or in the afternoon compared with early morning. This was expected because early starting schedules, such as from 3:00 a.m. to 6:59 a.m., interferes with circadian low points that occur from 2:00 a.m. to 6:00 a.m. This is consistent with the findings that drivers may not be fully refreshed and awake when they begin their workdays (Barr et al. 2005). The effects of time on the job showed increasing collision risk for driving longer hours without enough off-duty time. In addition, the results showed that drivers who work split runs have higher relative crash risks than the drivers who work straight runs. The group of operators working split runs has long driving hours and early start and late ending times. These are the characteristics of work schedules that lead to fatigue. It is obvious that split runs cannot be avoided. This study recommends that schedules be optimized with an objective of minimizing the length of split runs. Based on the results of this study, FDOT may further investigate reductions of the maximum driving hours of transit operators. The current Florida limits are higher compared with federal limits that govern trucks and interstate buses. Further research is needed to study the influence of the factors that were not included in this study, such as route length, vehicle characteristics, and driver characteristics, among other factors.

APPENDIX A: Transit Agencies Used in the Study

Agency Name	Location	Fleet size	Number of drivers
Jacksonville Transit Authority (JTA)	Jacksonville	129	268
Lynx	Orlando	274	396
Regional Transit System (RTS)	Gainesville	80	148
StarMetro	Tallahassee	105	160

APPENDIX B: Description of Variables

Variable	Dummy variable	Abbreviation	Range	Description
Schedule Start Time (ST)	Start Time Category 1	ST 1	3:00 a.m-7:00 a.m	1 if ST 1
	Start Time Category 2	ST2	7:00 a.m-11:00 a.m	2 if ST 2
	Start Time Category 3	ST 3	11:00 a.m-3.00 p.m	3 if ST 3
	Start Time Category 4	ST4	Later than 3.00 p.m	4 if ST 4
Total Off Duty Hours (OFF)	Off Duty Category 1	OFF 1	Less than 8 hours	1 if OFF 1
	Off Duty Category 2	OFF 2	8 – 12 hours	2 if OFF 2
	Off Duty Category 3	OFF 3	13 – 16 hours	3 if OFF 3
	Off Duty Category 4	OFF 4	More than 16 hours	4 if OFF 4
Total Hours on Task (TOT)	Total Time on Task Category 1	TOT 1	Less than 8 hours	1 if TOT 1
	Total Time on Task Category 2	TOT 2	8 – 12 hours	2 if TOT 2
	Total Time on Task Category 3	TOT 3	13 – 16 hours	3 if TOT 3
	Total Time on Task Category 4	TOT 4	More than 16 hours	4 if TOT 4
Schedule Type	Continuous Schedule	CON	Varies	0 if CON
	Split Schedule	SPL	Varies	1 if SPL

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Truck Use on Texas Toll Roads

by Dan P.K. Seedah, Joshua C. Muckelston, and Robert Harrison

Metropolitan toll roads are a popular source of non-traditional funded highway investment, targeting automobile users. Toll rates have been traditionally derived from traffic and revenue (T&R) studies, which appear unable to accurately estimate truck demand even when a toll road offers an alternative route segment to interstate trucking. This paper examines the current failure of Texas toll road SH-130 to attract truckers from IH-35 in Austin, one of the most congested Texas corridors. CT-VCOST, a comprehensive vehicle operating cost toolkit, was used to calculate truck operating costs on both highways to investigate why few truckers are using the toll facility and whether the decision is based on toll rates or other factors.

INTRODUCTION

Transportation is characterized by substantial capital investment needs, variability in both demand and energy costs, and modest profitability. Those providing transportation services over a specific transportation network—such as running trucks on highways—have to carefully control costs to provide competitive services. Where the operator builds, maintains, and controls the use of the infrastructure (such as railroads), management has full control of when to undertake optimal maintenance and replacement by balancing revenue needs and timing.

When one entity provides the infrastructure and others use it, as with highways, the picture is more complicated. Typically, in providing public highways, costs are allocated among the various classes of users to reflect a degree of equity although such allocation can lead to alleged cross-subsidization biases, which favor trucks (Kapoor et al. 2005, Bilal et al. 2010, Parry et al. 2012). The pricing of trucks, whether on public or toll roads, is relatively primitive and bears little relationship to the metrics used by highway engineers when designing the pavements and bridges over which trucks operate. For example, pavement engineers use forecasts of equivalent standard axle loads over the lifecycle of a highway section to determine subgrade, materials, and layer thickness. The pricing of truck use on public roads is limited to average vehicle miles of travel (VMT) per truck category and fuel taxes, even though fuel consumption is weakly correlated with overweight axles. The toll road featured in this paper, SH-130, actually uses fixed prices on axle numbers, not axle or gross weight, a method that spans over 100 years.

The funding of public highways is predicted to worsen through (a) reductions in both auto and freight VMT, (b) adoption of hybrid technologies reducing fuel consumption, and (c) improved truck aerodynamics and the use of lower rolling resistance tires. Consequently, a number of states are evaluating the use of tolled facilities managed and operated either by the states or private-public partnerships. The evidence from traffic and revenue (T&R) studies suggests that many tolled highways are priced to stimulate auto use and not truck use. This may be appropriate for metropolitan tolls. But in those cases where trucks comprise part of the target users, T&R studies are unable to estimate either costs or benefits facing truckers contemplating toll road use. Clearly, benefits such as on-time delivery and customer satisfaction must exceed the per-mile cost of using tolled routes since most tractor-trailer drivers are paid by the mile.

Truck toll road use comprises several factors, which are dynamic and need to be incorporated into toll pricing. Where the benefits are clear for all trips, truckers will use the facility. They will also use it if an alternative highway is blocked or experiencing heavy delays and they have time-sensitive cargo. This paper argues that toll road authorities may fail in adequately estimating truck operating costs and inadvertently set prices that act as disincentives to truck use. The literature, however, shows that there are a relatively small number of cost models that can be used by toll authorities to set truck rates. The objective of this study is to introduce a methodology that can be used to determine truck operating cost over any user-defined route profile. A case study is also presented that illustrates how planners and toll entities can determine which routes trucking companies will choose based on factors such as distance, travel time, congestion levels, travel speeds, toll charges, and pavement conditions.

BACKGROUND

In 2003, a Minnesota Department of Transportation (MnDOT) commissioned report was released on the per-mile cost of truck and automobile operation (Barnes and Langworthy 2004). This cost estimate focused on variable rather than fixed costs as MnDOT sought to use it as a tool to compare costs in traffic planning—for example, a congested corridor versus a longer but less congested route. The study investigated the costs of both personal vehicles and commercial trucks. The cost estimate consisted of five main factors: fuel, routine maintenance, tires, unanticipated repairs, and depreciation. Because vehicle operating cost (VCOST) estimates are mileage-based costs, Barnes and Langworthy (2004) based depreciation cost solely on mileage, which is lower than a vehicle's overall depreciation, which is also based on the age of the car. The MnDOT VCOST analysis differs from many others in that it takes into account the lifecycle costs of cars. For example, Consumer Reports (2011), Intellichoice (2011), and Edmunds (2011) only take into account the first four-five years of vehicle life. The study also considered highway, urban, and congested-urban traffic conditions, as well as pavement roughness, via the use of multiplicative adjustment factors. The MnDOT report provided VCOST estimation flexibility as a spreadsheet calculation tool that can be adapted to future conditions rather than a static estimate that is prone to obsolescence.

Based on the literature (Levinson et al. 2005, Berwick 1997, American Transportation Research Institute (ATRI) 2011) it can be inferred that a key missing component of VCOST pertinent to transportation planning is the ability to determine operating costs over different route profiles. While emphasis has been laid on pavement conditions (Zaabar and Chatti 2010, Texas Research and Development Foundation (TRDF) 1982, Walls and Smith 1998), only the work by Barnes and Langworthy (2004) addresses route-based VCOST. However, the MnDOT approach involves many approximations, and did not analyze truck operating costs with as much detail and depth as the analysis for personal vehicles (Welter et al. 2011).

The wide variety of vehicle technologies adopted over the past 15 years rendered the last VCOST model developed in Texas (TRDF 1982) obsolete, and in 2006 the Texas Department of Transportation (TxDOT) conducted a study to update VCOST estimates (Matthews et al. 2012). The model, termed CT-VCOST, is a comprehensive vehicle operating cost toolkit capable of producing an array of results that allows planners to better estimate the economic consequences of various highway investment strategies. It has a software that is user-friendly and provides operating cost estimates for specific representative vehicles or vehicle fleets. It utilizes a unique vehicle identifier algorithm for data storage, cost calculations, and user interactions via its graphical user interface. This unique identification property also enables vehicles to retain their unique data values when dealing with multiple vehicles, vehicle classes, and vehicle fleets.

The toolkit's default data are based on verified secondary vehicle cost data and certified vehicle databases such as the EPA's Fuel Economy database and Annual Certification Test Results databases. The toolkit also allows users to change the parameters so that cost calculations are specific to any particular situation, and can be updated as the economic or technological landscape changes. Cost categories in the CT-VCOST toolkit include those associated with depreciation, financing, insurance, maintenance, fuel, driver, road use fees (e.g., tolls), and other capital costs such as annual vehicle registration and inspection fees. Analysis types that can be performed with CT-VCOST include single vehicle analysis, multi-vehicle comparisons, fleet vehicle analysis, growth rate and market penetration simulation, and route cost analysis. It also comes packaged with sophisticated fuel economy prediction models for heavy duty, light duty, and hybrid vehicles. The fuel prediction models, developed using both experimental and survey data, have the ability to measure fuel consumption for default or custom drive cycles specified by users. Outputs from the fuel prediction models can be used within the toolkit to perform route cost analyses, an example of which is presented as a case study in this paper. In summary, CT-VCOST was designed to be intuitive and flexible enough for simulating different scenarios and situations that planners may envision. CT-VCOST is updatable and can be calibrated for any state or region.

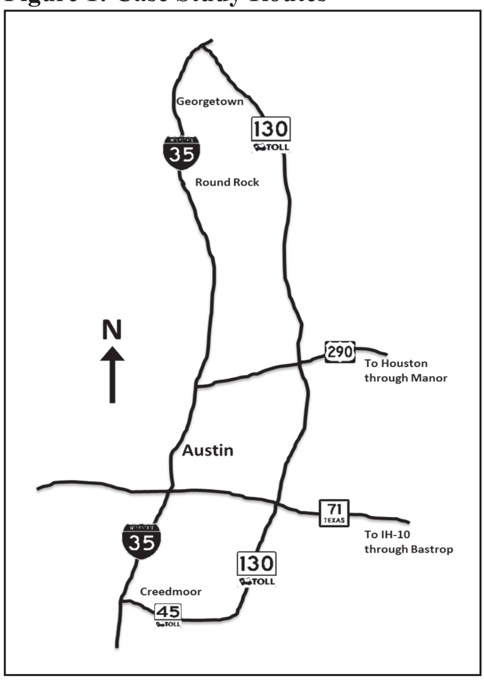
This paper shows that CT-VCOST can be used to determine truck operating cost over any user-defined route profile. A case study is also presented that illustrates how planners and toll entities can use CT-VCOST to determine which routes trucking companies will choose based on factors such as distance, travel time, congestion levels, travel speeds, toll charges, and pavement conditions.

CASE STUDY

As illustrated in Figure 1, Texas State Highway 130 (SH-130) connects with Interstate Highway 35 (IH-35) near Georgetown in the north and Buda in the south. SH-130 is being extended to reach Intestate Highway 10 (IH-10) near San Antonio in 2013. Currently, it is linked to IH-35 south by a toll road, State Highway 45 (SH-45). Critical for truckers, the SH-45/SH-130 route is approximately 12 miles longer than the alternate route on IH-35, even though travel times are shorter on it over much of a 24-hour period. The highway is a state-owned toll road and its extension is being developed in partnership with the toll road authority, the SH-130 Concession Company (TxDOT 2011a,b). Rapid growth in the city of Austin has led to an increase in congestion on IH-35, thus impacting transportation services to regions north and south of the city.

TxDOT representatives state that SH-130 has recorded both successes and failures in its effort to relieve congestion in Austin (Woodall 2011). SH-130 is servicing an acceptable amount of automobiles but TxDOT has not seen the same result for freight vehicles. A survey of trucking companies revealed that lowering toll rates on the highway could draw more freight vehicles but the elasticity of the toll rates was not determined (TheTrucker.com 2011). However, not all truckers are convinced that using this alternative tolled route has tangible benefits (Woodall 2011, New 2012). For example, even though IH-35 is shorter, some drivers have asserted that even if the toll were free, they will still not use it (Woodall 2011). In addition, it currently costs a six-axle truck with one truck and one trailer nearly $20 more to travel from SH-130's intersection with IH-35 south (via SH-45) to the SH-130 intersection with IH-35 north (TxTag 2011) (see Figure 1). Despite the inability of the toll facility to attract through truck traffic, a growing number of truckers use it when going east toward Houston via U.S. Highway 290 or to IH-10 via State Highway (SH-71) (see Figure 1).

Figure 1: Case Study Routes



Using CT-VCOST, it is possible to determine the actual cost and benefit of a route compared with another to evaluate the claims made by truckers. The following five existing routes were investigated and each was evaluated for both free flow and congested traffic conditions:

1. Through truck traffic through Austin using IH-35 versus SH-130
2. Northbound truck traffic using IH-35 or SH-130 to State Highway 71 East (SH-71E)
3. Southbound truck traffic using IH-35 or SH-130 to SH-71E
4. Northbound truck traffic using IH-35 or SH-130 to US Highway 290 East (US 290E)
5. Southbound truck traffic using IH-35 or SH-130 to US 290E

Comparing the costs to travel on these routes offers an understanding of why truckers prefer one route over another and also provides toll authorities with more accurate and equitable prices to stimulate truck demand, benefiting both the toll road and traffic flow on IH-35.

Toolkit Principles and Case Study Input

The CT-VCOST toolkit utilizes an object-oriented programming structure where "modules" are developed to perform particular tasks. For this case study, the following modules were used: the Scenario module, the Vehicle Utilization module, the Vehicle Maintenance module, and the Route Cost module. Pavement roughness for each roadway section can also be defined in the Route Cost module. The following sections of this paper discuss the modules and data used for this case study.

Vehicle Selection. The CT-VCOST database enables users to select from data reported on more than 5,000 default vehicles in the United States. Vehicles can be selected either by vehicle class, model, or year. If a vehicle cannot be found in the database, a custom vehicle can be built by the user and included in the database. For this case study, a custom Class 8 truck made up of a single wide-base tire tractor-trailer is used. Single wide-base tires are known to improve the fuel efficiency and stability of heavy-duty tractor-trailer trucks (Oak Ridge National Laboratory 2006). This particular vehicle was chosen because data for its fuel consumption measured in miles per gallon (mpg) as function of speed were readily available (Capps et al. 2008). Fuel cost calculation, discussed later in this paper, utilizes these kind of data.

Defining a Scenario. Once a vehicle is selected, a scenario must be defined using the Scenario module. This module enables users to input general parameters that influence VCOST such as the analysis period and fuel price. The analysis period defines the life span of the vehicle involved in the analysis. The specified number of years is used in determining the cut-off points for calculations such as vehicle depreciation, vehicles miles traveled, and scheduled maintenance. For this case study, an analysis period of 10 years is used. A diesel fuel price of $3.94 is also specified for this case study.

Vehicle Age and Utilization. As vehicles age, they tend to be driven less than newer vehicles (U.S. Department of Energy 2011) so the Vehicle Utilization module was developed to capture this change in vehicle use (annual mileage) over time. Users are able to input a vehicle's annual mileage for each year of its life span. Default data correlating vehicle utilization with age for passenger vehicles are available from the Transportation Energy Data Book (U.S. Department of Energy 2011) but data for trucking companies are much more difficult to find. Due to this limitation, truck utilization over the 10-year period of this case study is kept constant at 100,000 miles each year.

Maintenance and Repairs. The Vehicle Maintenance module seeks to simulate the actual maintenance activities of a vehicle. CT-VCOST enables maintenance activities to be set to either exact or range, depending on whether the maintenance activity occurs at a fixed mileage or within a certain mile range. For example, an oil change usually is performed at 10,000 miles for trucks; tire replacement varies between 50,000 to 100,000 miles per tire.

The difference between the two calculations is that with the exact interval option, repair cost is included in the cost calculation at the exact time the vehicle reaches the specified mileage. However, with the range interval, repair cost is distributed among the years between which the vehicle's mileage falls. For example, if tires need to be replaced somewhere between 60,000 and 100,000 miles, tire replacement costs are distributed equally between the years.

In addition, a repair may be set to be recurrent, which means that at the specified scheduled interval, the repair item will occur again. Using the tire replacement repair as an example, tire repair costs will be calculated again when the vehicle mileage reaches between the 120,000 to 200,000 mile range (see Figure 2). Using industry estimates for annual maintenance cost (ATRI 2011), this case utilizes the following maintenance schemes and cost:

- Oil change – every 10,000 miles at $600
- Tire replacement – every 100,000 miles at $2,600
- Scheduled service – every 100,000 miles at $6,000

Figure 2: Recurrent Tire Replacement Between 40,000 and 60,000 Miles and Corresponding Annual Maintenance Cost

Item Name	Schedule Interval		COST	Recurrent
Oil Change	Exact	10,000 miles	$600.00	Yes
Tire Replacement	Range	60,000 to 100,000 miles	$2,600.00	Yes
Hybrid Battery Replacement	Exact	0 miles	$0.00	No
Scheduled Service 1	Exact	100,000 miles	$6,000.00	Yes
Scheduled Service 2	Exact			
Scheduled Service 3	Exact			
Scheduled Service 4	Exact			
Scheduled Service 5	Exact			
Scheduled Service 6	Exact			
Scheduled Service 7	Exact			
Scheduled Service 8	Exact			
1st Major Repair Service	Range			
2nd Major Repair Service	Range			
3rd Major Repair Service	Range			
4th Major Repair Service	Range			
5th Major Repair Service	Range			

Year	Annual Maintenance Cost
Year 1	$14,600.00
Year 2	$12,000.00
Year 3	$12,000.00
Year 4	$14,600.00
Year 5	$12,000.00
Year 6	$12,000.00
Year 7	$12,000.00
Year 8	$14,600.00
Year 9	$12,000.00
Year 10	$12,000.00

Fuel Consumption. CT-VCOST is packaged with two different algorithms to calculate fuel consumption as a function of vehicle speed: 1) the slope-based approach and 2) the lookup table approach.

Slope-Based Approach. Fuel consumption, $f(v)$ is calculated as a function of speed v (i.e. $f(v)$), using at least two points: city miles per gallon (mpg_{city}) and highway miles per gallon (mpg_{hwy}). This approach assumes that mpg_{city} and mpg_{hwy} are achieved at average speeds of 21.2 mph ($\bar{v}_{city}$) and 48.3 mph ($\bar{v}_{hwy}$) respectively according to EPA test results (EPA 2011). The user then specifies an optimum fuel consumption speed (v_o) and using Equations 1 and 2, the possible fuel consumption estimates are calculated. Equation 1 determines fuel economy at any speed (v) by using a linear function, which is dependent on whether v is: (a) lesser than or equal to optimum speed (v_o), or (b) v is greater than optimum speed (v_o). If $v \leq v_o$, fuel consumption $f(v)$ will be between the vehicle's EPA specified city miles per gallon (mpg_{city}) and highway miles per gallon (mpg_{hwy}), where mpg_{hwy} is assumed to be equal to the optimum fuel economy $f(v_o)$. The slope (m) is determined by the corresponding highway and city fuel consumptions mpg_{hwy}, mpg_{city}) and speeds ($\bar{v}_{hwy}$, $\bar{v}_{city}$). To ensure that $f(v_o)$ remains the optimum (or maximum) fuel consumption, fuel consumption $f(v)$ is calculated using a negative slope when $v > v_o$. As illustrated in Figure 3, the slope-based approach, though simple and replicable for most vehicles, is not entirely accurate as optimum fuel consumption varies between 25 to 55 miles per hour when using actual fuel economy data.

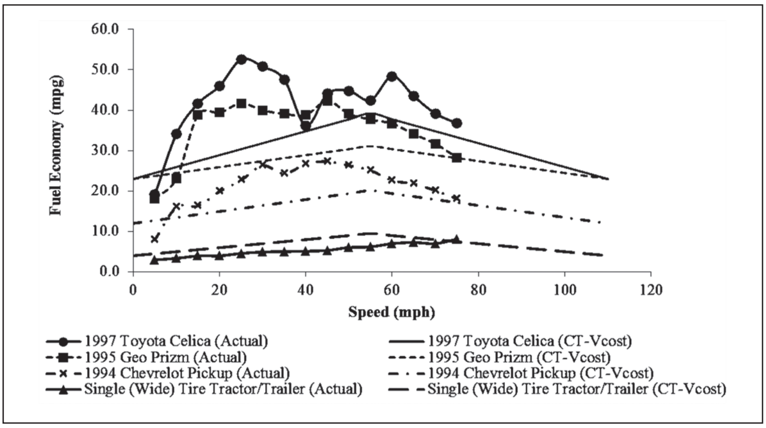
$$(1)\quad f(v) = \left\{ \begin{array}{ll} (v * m) + mpg_{city} & if\, v \leq v_o \\ f(v_o) - m\,(v - v_o) & if\, v > v_o \end{array} \right\}$$

$$(2)\quad m = \frac{mpg_{hwy} - mpg_{city}}{\bar{v}_{hwy} - \bar{v}_{city}}$$

Lookup Table Approach. The lookup table approach provides a much better estimate of fuel consumption as function of speed (see Table 1). This approach, though more accurate, is dependent on the availability of data. For each speed (v) on the specified route profile, CT-VCOST iterates through each row of the column matching the vehicle model and returns the vehicle's fuel consumption, $f(v)$ using linear interpolation. When the vehicle speed (v) falls within the range of two successive speeds $[(v_i)$ and $(f(v_{i+1})]$, the fuel consumption for those speeds $f(v_i)$ and $(f(v_{i+1})$ are used in determining the vehicles' fuel consumption $f(v)$ as illustrated in the linear interpolation shown in Equation 3.

$$(3)\quad f(v) = \left[\left(\frac{f(v_{i+1}) - fv_i)}{v_{i+1} - v_i} \right) \times (v - v_i) \right] + f(v_i)$$

Figure 3: Comparison of Slope-Based Approach With Actual Fuel Economy Data



(Source: Matthew et al. 2011)

Driver Costs. CT-VCOST provides users with two alternatives for capturing driver cost: Hourly driver cost and per-mile driver cost. Hourly driver cost captures the cost of delay during congested conditions. This is useful for time sensitive deliveries such as perishables and high value commodities. This case study however uses only the per-mile driver cost as it represents the majority of truckers using IH-35 (Woodall 2011). An industry average value in 2010 of $0.40 a mile is used (ATRI 2011).

Depreciation, Financing, Insurance, Registration, and Permit Fees. Typical vehicle depreciation for light-duty vehicles was found to be at around 20% for the first year and 15% or less for the subsequent years (Sandler 2003, Edmunds.com 2011). This assumption was used for this case study due to lack of credible data for heavy-duty vehicles. Financing was also based on a 1.5% down payment and a 60-month loan at an interest rate of 4.55%. The insurance cost was based on industry estimates, which ranged from $4,000 to $7,500 annually. A value of $5,500 is used for this case study. Registration and permit fees were calculated using industry estimates (ATRI 2011), and an annual value of $2,300 was assigned.

Specifying Route Conditions. The route cost module enables users to simulate the cost of moving a vehicle or a fleet of vehicles via certain routes. Multiple routes and their characteristics such as distance, speed, congestion level, pavement roughness (Zaabar and Chatti 2010), and travel time are defined by the user. VCOST via each route is then calculated and presented for comparison.

Table 1: Sample Fuel Economy Lookup Table in MPGs

Speed (mph)	1994 Chevrolet Pickup	1994 Jeep Grand Cherokee	1997 Toyota Celica	Dual Tire Tractor - Dual Tire Trailer	Dual Tire Tractor - Single Wide Tire Trailer	Single Wide Tire Tractor - Dual Tire Trailer	Single Wide Tire Tractor - Single Wide Tire Trailer
5	7.9	8.2	19.1	2.8	2.9	3.0	3.0
10	16.0	11.2	34.1	3.4	3.6	3.3	3.4
15	16.3	17.5	41.7	3.8	4.0	3.9	4.0
20	19.9	24.7	46.0	3.7	4.0	4.0	4.0
25	22.7	21.8	52.6	4.1	4.3	4.6	4.6
30	26.3	21.6	50.8	4.4	4.6	5.0	4.9
35	24.3	25.0	47.6	4.4	4.9	5.2	5.0
40	26.7	25.5	36.2	4.8	5.2	5.3	5.1
45	27.3	25.4	44.1	5.1	5.4	5.6	5.3
50	26.3	24.8	44.8	5.4	5.8	6.2	6.0
55	25.1	24.0	42.5	5.8	6.1	6.2	6.2
60	22.6	23.2	48.4	6.3	6.8	6.9	7.0
65	21.8	21.3	43.5	6.6	7.2	7.1	7.3
70	20.1	20.0	39.2	7.0	7.7	7.0	7.0
75	18.1	19.1	36.8	7.5	7.9	7.9	8.1

Table 2 presents all the case study routes and their respective characteristics while Table 3 summarizes the input data. Traffic conditions from Google Maps for both routes at 7:30 a.m. were used for the congested scenarios in this case study.

Case Study Findings

In this case study, it was determined that total route cost was dependent on distance, speed, fuel consumption, and per-mile driver cost. Based on average 2008 fuel prices of $3.814 a gallon (U.S. Energy Information Administration [EIA] 2011), the American Transportation Research Institute (2011) reported average truck fuel and oil cost to be $0.63 per mile. In comparison, per-mile fuel cost from CT-VCOST for this case study ranged between $0.56 to $0.77 per mile. Additional dependent variables that CT-VCOST could have captured but were not considered in this case study include pavement roughness and hourly driver cost.

Annual cost variables found to be independent of route cost were depreciation, finance, insurance, maintenance (including tires), and other costs (vehicle registration and permits). Per-mile cost for each of these variables were $0.09, $0.13, $0.05, $0.14, and $0.02, respectively ($0.43 total). Similar per-mile cost reported by the American Transportation Research Institute (2011) for those same variables in the first quarter of 2010 were $0.21 (finance), $0.05 (insurance), $0.15 (maintenance and tires) and $0.02 (vehicle registration and permits).

IH-35 versus SH-130 Through Traffic. In this scenario, through truck traffic using 55 miles of SH-130 compared with 43.4 miles of IH-35 were analyzed. Under free flow conditions, per-mile cost (excluding toll charges) for both routes was found to be $1.40 (including $0.56 fuel, $0.40 driver cost). However, total route costs and travel time were found to be $77.06 and 55.20 minutes for SH-130, compared with $60.67 and 43.20 minutes for IH-35. The vehicle consumed 7.87 gallons

Table 2: Route Data Input for IH-35 / SH-130 Case Study

Route Name	Section	Distance (miles)	Condition	Speed (mph)	Travel Time (minutes)	Toll
IH-35 vs. SH-130 (through Austin)						
SH-130 (Free flow)		55.0	Free Flow	60	55.2	$19.20
IH-35 (Free flow)		43.4	Free Flow	60	43.2	–
SH-130 (2011 Cong.)		55.0	Free Flow	60	55.2	$19.20
IH-35 (2011 Cong.)	*Section 1*	4.0	Free Flow	60	4.2	–
	Section 2	7.9	Congested	24	19.8	–
	Section 3	31.5	Moderate	36	52.8	–
North Bound to SH 71 E						
SH-130 (Free flow)		25.0	Free Flow	60	25.2	$7.05
IH-35 (Free flow)		25.0	Free Flow	60	25.2	–
IH-35 (Congested)		5.0	Free Flow	60	4.8	–
	Section 1	5.0	Moderate	40	7.8	–
	Section 2	15.0	Free Flow	60	15.0	–
South Bound to SH 71 E						
SH-130 (Free flow)		47.0	Free Flow	60	46.8	$12.15
IH-35 (Free flow)		52.0	Free Flow	60	52.2	–
IH-35 (Congested)	*Section 1*	37.0	Free Flow	60	37.2	–
	Section 2	15.0	Moderate	45	19.8	–
North Bound to US 290 E						
SH-130 (Free flow)		32.0	Free Flow	60	31.8	$11.10
IH-35 (Free flow)		28.0	Free Flow	60	28.2	–
IH-35 (Congested)	*Section 1*	7.0	Free Flow	60	7.2	–
	Section 2	8.0	Moderate	40	12.0	–
	Section 3	5.0	Congested	20	15.0	–
	Section 4	8.0	Moderate	40	12.0	–
South Bound to US 290 E						
SH-130 (Free flow)	*Section 1*	28.0	Free Flow	60	28.2	$ 8.10
	Section 2	3.0	Free Flow	60	3.0	–
IH-35 (Free flow)	*Section 1*	30.0	Free Flow	60	30.0	–
	Section 2	10.0	Free Flow	50	12.0	–
IH-35 (Congested)	*Section 1*	20.0	Free Flow	60	19.8	–
	Section 2	5.0	Moderate	40	7.8	–
	Section 3	5.0	Free Flow	60	4.8	–
	Section 4	10.0	Free Flow	50	12.0	–

Table 3: Summary of Input Data

Variable	Input Data
Diesel price	$3.92
Utilization curve	Kept constant. Annual mileage was therefore 100,000 miles each year for 10 years
Maintenance cost (tire & oil change only)	Average Annual: $14,600 Average Per Mile: $0.15 per mile
Fuel economy calculation	Slope based approach
Driver wage	$0.40 per mile
Depreciation:	20% first year, 15 % subsequent years
Financing	1.5% down payment and a 60-month loan at an interest rate of 4.55%
Insurance	$5,500 a year
Registration and Permit Fees:	$2,300 a year
Toll charges	Based on 2011 values from Austin Toll Calculator (TxTag, 2011)
Vehicle Body Shape:	Tractor plus One Trailer
Vehicle Axle Count:	5 axle
Payment Type:	TxTag Electronic Toll Tag

of fuel on SH-130 compared with 6.21 gallons on IH-35. Under current 2011 congested conditions, per-mile costs were found to be $1.40 for SH-130 and $1.58 for IH-35. Fuel cost, gallons of fuel, driver cost, and travel time remained unchanged for SH-130, as it does not currently experience any congestion. However, total route cost and travel time on IH-35 increased by $7.75 and 33.60 minutes, respectively. Gallons of fuel consumed, per-mile fuel cost and driver costs increased by 1.98 gallons, $0.18, and $4.69, respectively, on IH-35. Based on the above analysis, it can be inferred that IH-35 is the most favorable route for free flow conditions and non-time sensitive commodity flows. Despite the congested conditions on IH-35, it still costs drivers $8.64 more (excluding tolls) to use SH-130 because of the additional 11.6 miles they have to drive on SH-130. If the $19.20 toll is accounted for, drivers will have to pay an additional $27.84 to use SH-130 instead of IH-35.

Northbound and Southbound Traffic to SH-71E via IH-35 and SH-130. This scenario sought to determine if truckers may prefer to use SH-130 instead of IH-35 when heading east to Bastrop via SH-71. During free flow conditions for northbound traffic, total route cost and travel time for both IH-35 and SH-130 to SH-71E were both the same ($35.03 and 25.20 minutes respectively) because both routes have similar distances. However, if the toll charged on SH-130 is included in the total route cost, SH-130 was $7.05 more costly than IH-35. Per-mile cost (excluding toll charges) was $1.40, fuel consumed was 3.58 gallons, and per-mile fuel cost was $0.56. For congested conditions, per mile fuel cost increased to $0.63 for IH-35, thus increasing total route cost by $1.73. Travel time on IH-35 also increased by 2.40 minutes.

For southbound traffic, route distance to SH-71E via SH-130 was 47 miles and that of IH-35 was 52 miles. Per-mile cost (excluding toll charges) was $1.40 for both routes, and total fuel consumed was 6.72 and 7.44 gallons for SH-130 and IH-35, respectively. During free flow conditions, total route cost on IH-35 was determined to be $72.82 ($7.00 more than SH-130). However, if the $12.15

toll charged on SH-130 is included, then using SH-130 will cost $5.15 more than using IH-35. For congested conditions, total route cost on IH-35 increased by $4.62, thus costing $11.62 more to use IH-35 instead of SH-130.

Northbound and Southbound Traffic to US-290E via IH-35 and SH-130. Similar to the SH-71E analysis, the US-290E scenario sought to determine if truckers may prefer to use SH-130 instead of IH-35 when heading east to Houston. For northbound free flow conditions, it was determined that it costs drivers $5.61 more (excluding tolls) to use SH-130 instead of IH-35 because of the additional four miles that need to be driven. Including tolls, drivers have to pay $16.71 more to use SH-130 instead of IH-35. In congested conditions, the difference in total route cost between SH-130 and IH-35 decreases to $3.66 (excluding tolls) or $14.76 when including tolls. Per-mile fuel cost for IH-35 increased by $0.21 and total driver cost increased by $1.62.

For southbound traffic, route distance to US-290E via SH-130 was 31 miles and that of IH-35 was 40 miles. It was determined that for both free flow and congested conditions, SH-130 was the more favorable route despite the additional $8.10 toll. IH-35 cost drivers an additional $5.00 even when SH-130 is tolled or $13.00 when SH-130 is not tolled.

CONCLUSION

CT-VCOST was developed so planners at the Texas Department of Transportation could better estimate the economic consequences of various engineering strategies and assist in policy making. CT-VCOST can be used, with minor calibration, in any state or region where a transportation planning entity needs to examine policies relating to setting toll charges, projecting future fuel consumption and fuel tax revenue, and examining the effects of pavement condition on vehicle operating costs.

CT-VCOST was used in validating claims by truck drivers concerning the use of the SH-130 toll facility, which runs parallel to IH-35. Despite congested conditions on IH-35, drivers pay an additional $27.84 when using the tolled SH-130 facility when traveling through Austin. Should the current toll of $19.20 not exist, drivers will still pay an additional $8.64 when using SH-130 because of the extra 11.6 miles they must drive.

Northbound traffic to SH-71E via SH-130 was competitive to IH-35 both in terms of cost and travel time. However, the additional $5.15 toll on SH-130 could be a disincentive to truck drivers if travel time is not a factor. For southbound traffic to SH-71E, IH-35 was less costly than the tolled facility on SH-130 but drivers experienced greater travel time delays especially in congested conditions.

Northbound traffic to US-290 E favored IH-35 more than SH-130 during both congested and free flow conditions from a cost-only perspective (IH-35 cost $16.90 less). However, travel time on IH-35 was 14.4 minutes more than SH-130 during congested periods. Southbound traffic, on the other hand, favored SH-130 as it remained less expensive ($4.50) and faster (13.2 minutes) than IH-35 even in congested conditions.

In summary, it can be inferred from CT-VCOST and the case study that not all new tolled facilities are setting prices favorable to truckers from a cost saving perspective. This is not simply a case of overestimating truck toll fees – which is generally the case with current traffic and revenue analysis – but may occur even when the toll is set at zero. However, for deliveries where travel time is a major consideration, using tolled facilities seems beneficial if the cost associated with using the facility does not offset the time savings. In addition, most truck drivers are paid by the mile, and longer tolled routes are a disincentive in comparison with the shorter and free alternative route because of additional mileage and toll fees. Truckers are rational and toll authorities should be using updated—even dynamic—vehicle operating cost information to induce truck demand. Truck toll road pricing should be substantially more equitable and based on fuel consumption and congestion impacts.

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Correlation Analysis of Duty Cycle Effects on Exhaust Emissions and Fuel Economy

by Jun Tu, W. Scott Wayne, and Mario G. Perhinschi

Correlation analysis was performed to investigate the effects of drive cycle characteristics on distance-specific emissions (g/mile) and fuel economy (mpg) and consequently determine the most influential cycle metrics for modeling. A detailed analysis of linear and non-linear correlations was performed among cycle metrics to avoid collinearity and reduce the number of variables. The order of importance of the selected cycle metrics was determined. Results show that average speed with idle, number of stops per mile, percentage idle, and kinetic intensity were the most important cycle metrics affecting emissions and fuel economy. Preliminary regression analysis reinforced their importance for emissions modeling purposes.

INTRODUCTION

West Virginia University (WVU) has been engaged in developing an Integrated Bus Information System (IBIS) (Wayne et al. 2011) for the Federal Transit Administration (FTA). The intent of IBIS is to provide information on emissions and fuel economy for available bus technologies for bus procurement activities. IBIS includes a database of emissions test results of transit buses, a bus fleet emissions model, and a life cycle cost model. Compared with existing major emission models, such as the Mobile Source Emission Factor Model (MOBILE6) (U.S EPA 2003), the Motor Vehicle Emission Simulator (MOVES) developed by the U.S. Environmental Protection Agency (U.S. EPA 2010), IBIS provides transit agencies a simple tool to satisfactorily estimate emissions for evaluating the impact of new vehicle procurement on the overall fleet emissions profile. Similarly, IBIS is simpler compared with the EMission FACtors (EMFAC) model developed by the California Air Resources Board (CARB 2006)

The purpose of this study is to investigate the drive effects of cycle characteristics, which are metrics based on second-by-second vehicle speed data and distance-specific emissions in order to identify the most important parameters that should be included in a predictive emissions model. These emissions are carbon monoxide (CO), carbon dioxide (CO_2), oxides of nitrogen (NOx), hydrocarbons (HC), and particulate matter (PM). This study is unique because WVU collected emissions data from 12 predefined vehicle speeds on the same vehicle using a chassis dynamometer. These speeds are the chassis dynamometer test cycles used in this study and are different from test or duty cycles in which a driver operates a bus on a chassis dynamometer to perform emissions testing. Data interpolation enabled the authors to investigate the statistical relationships between cycle metrics and their impacts on emissions and fuel economy (FE). In previous studies, data from only a limited number of test cycles on the same vehicle (typically five or less) were available, and this limited the effectiveness of their statistical analyses. This study identifies the most influential cycle metrics for inclusion in the IBIS emissions model as well as other emissions and fuel economy modeling efforts.

Driving characteristics are among the main factors affecting emissions and fuel economy of transit buses. Other important factors include vehicle parameters, fuel types, engine parameters, road conditions, and ambient conditions (Clark et al. 2002). To mimic actual driving conditions of on-road vehicles, chassis dynamometer cycles have been developed (Gautam et al. 2002, Nine et al. 1999). Previous studies, using emissions data from multiple test cycles, showed that distance-specific emissions depended strongly upon the characteristics of duty cycles and found that average speed was one of the most important cycle metrics (Graboski et al. 1998, Nine et al. 2000, Clark et al. 1997, Vora et al. 2004). The MOBILE6 and EMFAC models estimate emissions as a function of average speed. Specifically, these macroscopic models calculate emissions based on average speed and vehicle miles traveled. At different average speeds, the study used speed correction factors to estimate emissions. These speed correction factors are determined by fitting emissions values with average speed. Previous studies showed the insufficiency of using average speed to evaluate emissions since average speed alone could not comprehensively reflect cycle characteristics (Ahn et al. 2002, Rakha and Ding 2003). Other metrics besides average speed, such as percentage idle and average acceleration, have been investigated (Andre and Pronello 1997, Wayne et al. 2007, Clark et al. 2007, Khan et al. 2007, Rakha and Ding 2003). However, these studies did not discuss all important duty cycle metrics.

Thirteen cycle metrics were considered in this study. They are average speed with idle (or average speed) and without idle, number of stops per mile (stops/mile), percentage idle, standard deviation of speed with and without idle, average and maximum acceleration, average and maximum deceleration, aerodynamic speed, which is the difference between average cubed speed and average speed, kinetic intensity, and characteristic acceleration (O'Keefe et al. 2007). The latter, characteristic acceleration, is specific kinetic energy per unit mass and distance required accelerating a vehicle over a duty cycle after ignoring road grade effects. This acceleration is equal to the actual vehicle acceleration if the vehicle increases its speed at a constant rate. The square of aerodynamic speed directly reflects the effects of aerodynamics on fuel economy and it is equal to the actual vehicle speed from driving at a constant speed. Kinetic intensity relates to fuel savings of hybrid vehicles over their conventional counterparts tested on the same cycles, and it gives an indication of whether hybridization will result in fuel savings for a particular duty cycle. Kinetic intensity is the ratio of characteristic acceleration to the square of aerodynamic speed. A cycle with a larger characteristic acceleration and a smaller aerodynamic speed that results in higher kinetic intensity is better for hybridization (O'Keefe et al. 2007).

These 13 cycle metrics were analyzed by correlation to reduce the number of cycle metrics and remove those that are collinear. In selecting the metrics to use in the IBIS emissions model, the study considered the abilities of transit agencies to calculate their values using data available to them. In some cases, some metrics were retained or eliminated based on this additional criterion. To account for non-linear relationships, this study uses a non-parametric correlation analysis to determine the order of importance of the chosen metrics in predicting emissions and fuel economy. Preliminary regression analysis was performed to demonstrate and reinforce the significant effect of the selected cycle metrics for modeling. The JMP® statistical software (SAS Institute 2009, Freund et al. 2003) and MATLAB® were used for the data analysis, as well as correlation and regression analysis in this study.

TEST VEHICLE INFORMATION

A model year (MY) 2000 Orion diesel transit bus was tested at the Washington Metropolitan Area Transit Authority (WMATA) facility to compare the effects of different drive cycles on emissions. The bus had a gross vehicle weight rating (GVWR) of 42,540 pounds and a curb weight (the weight of a bus without passengers but with all of standard equipment) of 28,800 lbs. The weight as tested was 33,300 pounds, representing half-seated passenger load. The test bus was powered by a 2000 MY, 8.5-liter, 4-cylinder, and 275 horsepower Detroit Diesel S50 engine with a diesel oxidation catalyst (DOC). The fuel used by the bus was type one ultra-low sulfur diesel (ULSD1). The vehicle was equipped with a four-speed Voith D863 automatic transmission. The vehicle configuration remained the same for all test cycles. The bus was tested over 12 test cycles, which are described in the following section.

TEST CYCLES

Multiple chassis dynamometer test cycles (Clark et al. 2002, DieselNet 2007, SAE International 1982, SAE International 2002, Schiavone et al. 2002, Thompson et al. 1990, Wayne et al. 2002) were used since emissions and fuel economy are related to duty cycles. Since it is not practical to develop test cycles for all types of vehicles and driving behaviors, it is necessary to develop a limited but representative number of test cycles to mimic driving activities of realistic transit bus operation. Specific test cycles were generated to represent real-world operation in specific applications or localities. For example, the New York Bus cycle (NYBus) (Clark et al. 2002) was developed to represent the driving conditions of heavy-duty vehicles in New York City. The test vehicle was operated through 12 chassis dynamometer cycles for this study, and multiple repeat runs were performed on certain test cycles. In total, 13 cycle metrics were considered in this study. The test cycles and their characteristics are summarized in Table 1 and cycle abbreviations are defined in Appendix A at the end of this paper.

EXTENDED DATABASE

Since only 12 cycles were available for analysis, an expanded database was desired. Figure 1 shows carbon monoxide emissions as a function of cycle average speed ranging from the lowest speed of 3.57 miles per hour (mph) (NYBus cycle) to the highest speed of 43.72 mph (COMM cycle) (SAE International 1982). No test cycles existed between an average speed from 28.63 mph (ETC cycle) (DieseltNet 2007) and 43.72 mph (COMM cycle). Interpolation was used to extend the database to fill the gaps as mentioned above with the assumption that no extreme cycle characteristics exist between adjacent cycle points. Initially, 18 cycle points were interpolated using an equal interval of two mph for the average speed. A piecewise cubic hermite interpolating polynomial (pchip) (Kahaner et al. 1988) was applied in this study using MATLAB®. The pchip polynomial is one type of piecewise cubic polynomials and it can be determined using both values from end-points and their derivatives. A comparison with other interpolation methods is provided in Figure 1. Compared with linear interpolation, pchip interpolation is smoother and less likely to overshoot. Although spline interpolation had smoother results than pchip, it was not considered because it caused more oscillation in data interpolation. The same analysis and method were applied to the four other cycle metrics. The magnitudes of the intervals were 10% for percentage idle, four stops per mile (stops/mile), three mph for standard deviation of speed, and one reciprocal of unit mile (mile-1) for kinetic intensity. In this way, 44 cycle points were generated to extend the database to 56 cycle points. When extended emissions and fuel economy data were plotted against duty cycle metrics, no significant deviation from the reference dataset was observed and the interpolated cycle points followed the same trend as the reference points.

ROAD LOAD DERIVED CYCLE METRICS

Unlike conventional cycle metrics derived directly from speed-time trace (second-by-second vehicle speed data), aerodynamic speed, characteristic acceleration, and kinetic intensity were derived from a road load equation (Gillespie 1992, Miller 2004) to relate them to fuel consumption (O'Keefe et al. 2007). The general form of the road load equation is:

(1) $$F_{traction} = M\frac{dv}{dt} + F_{aero} + F_{rolling} + F_{grade}$$

Table 1: Statistics of 12 Target Dynamometer Test Cycles

Cycle	Duration (seconds)	Distance Traveled (miles)	Average Speed with Idle (mph)	Average Speed without Idle (mph)	Percentage Idle	Number of Stops per Mile	Standard Deviation of Speed with Idle (mph)	Standard Deviation of Speed without Idle (mph)
ART	291.6	2.00	24.71	29.55	16.39%	2.00	15.64	12.19
BEELINE	1724	6.79	14.17	19.29	26.54%	3.54	14.74	14.04
BRAUN	1750	6.73	13.85	18.48	25.04%	4.31	11.35	9.30
CBD	586	2.01	12.36	15.71	21.35%	6.96	8.46	6.19
COMM	329.6	4.00	43.72	49.71	12.04%	0.25	19.46	11.46
ETC_12	1200	9.54	28.63	29.93	4.32%	0.42	15.84	14.95
MAN	1098.7	2.07	6.77	10.66	36.52%	9.68	7.33	6.56
NYBUS	620	0.61	3.57	10.69	66.60%	17.89	6.41	6.86
NY-COMP	1029	2.51	8.77	12.85	31.76%	7.58	9.44	8.84
OCTA	1950	6.54	12.08	15.52	22.17%	4.74	10.33	9.14
UDDS	1060	5.54	18.83	28.04	32.84%	2.89	19.82	18.07
WMATA	1839	4.25	8.32	13.47	38.27%	6.12	10.31	10.14

Cycle	Average Acceleration (ft/sec^2)	Maximum Acceleration (ft/sec^2)	Average Deceleration (ft/sec^2)	Maximum Deceleration (ft/sec^2)	Aerodynamic Speed (mph)	Characteristic Acceleration (ft/sec^2)	Kinetic Intensity (mile^{-1})
ART	2.02	3.67	6.45	7.33	35.58	0.65	1.26
BEELINE	2.06	7.33	2.58	10.27	32.03	0.88	2.10
BRAUN	2.08	8.07	2.80	11.73	24.17	0.72	3.02
CBD	2.87	3.67	6.38	7.33	18.55	0.57	4.04
COMM	1.37	3.67	6.67	18.33	52.84	0.15	0.14
ETC_12	1.14	13.20	1.26	8.07	39.16	0.31	0.50
MAN	2.04	7.33	2.59	8.80	15.78	0.94	9.24
NYBUS	4.09	9.53	2.39	7.33	16.64	1.25	11.07
NY-COMP	1.72	13.93	1.94	13.20	20.69	0.77	4.42
OCTA	1.88	5.87	2.61	8.07	22.10	0.72	3.60
UDDS	1.78	8.80	1.99	8.07	42.49	0.50	0.68
WMATA	1.74	4.40	2.10	6.60	23.22	0.77	3.51

Where $F_{traction}$ is the total traction required for vehicle motion, M is vehicle mass, dv/dt is vehicle acceleration, F_{aero} is aerodynamic resistance, $F_{rolling}$ is rolling resistance, and F_{grade} is grade resistance due to a slope. A detailed derivation and background information are provided in O'Keefe et al. (2007) and Simpson (2005).

Originally, these three cycle metrics were to be used with fuel consumption to differentiate duty cycles as well as fuel savings for hybrid vehicles on a given duty cycle (O'Keefe et al. 2007). Since they are derived from a road load equation and are related to energy usage, these cycle metrics are hypothesized to have some relationships with emissions and fuel economy.

Table 2 presents correlations of the metrics with distance-specific emissions and fuel economy, and it shows all three metrics have significant correlations. The negative correlations between aerodynamic speed and emissions indicate that emissions increase with decreasing aerodynamic speed, while the positive correlation with fuel economy shows that fuel economy increases along with increasing aerodynamic speed. However, characteristic acceleration as shown in Table 2 has an inverse relationship with the emissions and fuel economy compared with aerodynamic speed, which makes sense because larger characteristic acceleration requires more kinetic energy to accelerate, indicating higher fuel consumption and increased emissions. Kinetic intensity shows the same but stronger correlation trend as characteristic acceleration (except with fuel economy) compared with the other two metrics.

Figure 1: Reference Cycles and Comparison of Interpolation Curves Based on Average Speed

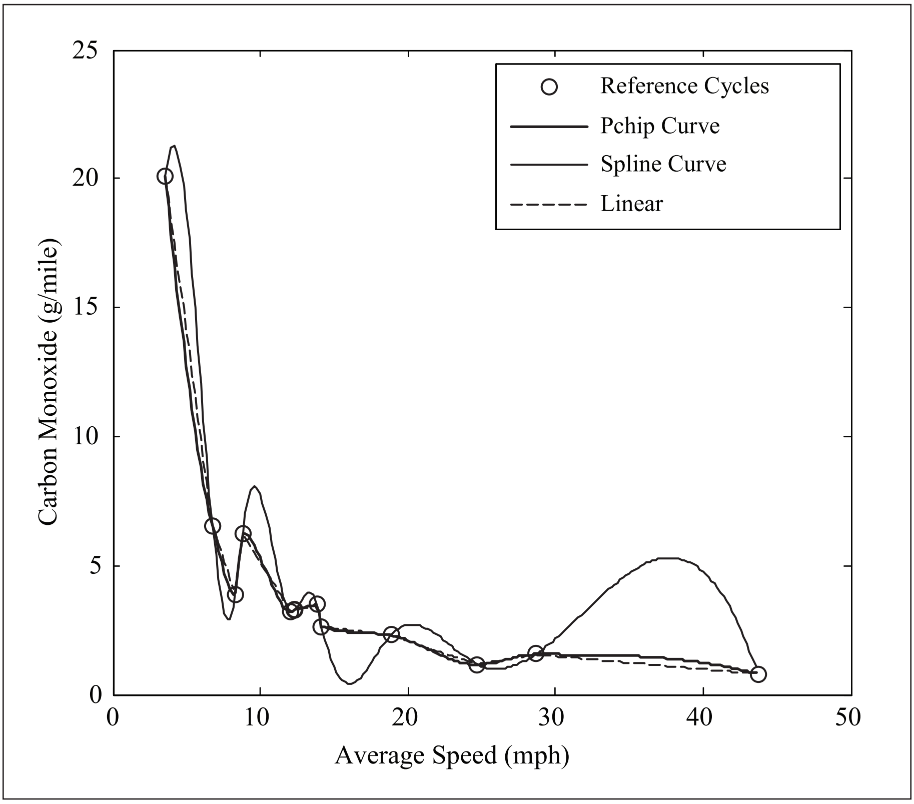


Table 2: Correlations of Road Load Derived Cycle Metrics With Emissions and Fuel Economy

	CO_2	CO	HC	NOx	PM	FuelEco
AeroV	-0.77	-0.70	-0.80	-0.66	-0.72	0.85
CharAcc	0.89	0.78	0.79	0.82	0.81	-0.94
KInt	0.94	0.89	0.93	0.87	0.90	-0.84

Note: All correlations are significant at the 0.0001 level ($p<0.0001$).

AeroV: Aerodynamic speed
CharAcc: Characteristic acceleration
KInt: Kinetic intensity
CO: Carbon monoxide
CO_2: Carbon dioxide
HC: Hydrocarbon
NOx: Oxides of nitrogen
PM: Particulate matter
FuelEco: Fuel economy

SELECTION OF THE IMPORTANT CYCLE METRICS

A detailed correlation analysis was performed to identify the duty cycle metrics having the most significant correlations with emissions and fuel economy and to detect highly correlated redundant metrics.

Correlation Analysis Among Cycle Metrics

A Pearson correlation matrix was applied to detect bivariate collinearity among the cycle metrics. The analysis shows that several variables highly correlate with each other. Although the existence of collinearity is not a violation of the assumptions of regression analysis, it shows that several cycle metrics have similar impacts on emissions and fuel economy and they should be removed from the analysis. Collinearity also makes it difficult to interpret the partial regression coefficients, which measure the effect of the corresponding cycle metrics while holding constant all other metrics. When collinearity exists, the affected coefficients estimate some effects for the response but not really from the corresponding metrics. Table 3 shows full correlation coefficients for the 13 duty cycle metrics. Statistically significant and strong correlations were found among some variables including the following:

a. Average speed with idle versus average speed without idle, aerodynamic speed, and characteristic acceleration;
b. Average speed without idle versus standard deviation of vehicle speed with idle, and aerodynamic speed;
c. Stops per mile versus percentage idle and kinetic intensity;
d. The standard deviations of vehicle speed with idle versus aerodynamic speed and standard deviation of vehicle speed without idle.

In total, nine pairs of metrics have correlations larger than 0.90 in absolute terms, which are statistically significant at probability levels of less than 0.0001. These pairs are highlighted with bold typeface letters in the lower triangular matrix in Table 3. Consistent with previous studies by Clark et al. (2002), Clark and Gajendran (2003), and Boriboonsomsin and Uddin (2006) that have concluded that average speed (with idle) is an important factor due to its relationship with other cycle properties, it is found that average speed with idle correlates with most cycle metrics. As a result, average speed without idle, aerodynamic speed, and characteristic acceleration were removed from the analysis. Average speed with idle was retained rather than average speed without idle because the former is easier for a transit agency to calculate. Similarly, the standard deviation of vehicle speed with idle has strong relationships with the standard deviation of vehicle speed without idle and aerodynamic speed, and it was retained, while the standard deviation of vehicle speed without idle was removed.

Aerodynamic speed correlates with both average speed and the standard deviation of vehicle speed, indicating that it may reflect the statistical features of vehicle speed such as the mean and dispersion. However, aerodynamic speed was removed, because average speed and standard deviation of vehicle speed were retained. Additionally, O'Keefe et al. (2007) showed that kinetic intensity is related to both aerodynamic speed and characteristic acceleration. Thus, it is better to retain kinetic intensity than aerodynamic speed or characteristic acceleration.

Since it reflects the transient nature of driving cycles and it is easily obtained, stops per mile were retained, as was the percentage idle because of its effects on emissions (Wayne et al. 2007), although both metrics strongly correlate with each other. However, this strong positive correlation cannot be well explained. For example, more stops in a trip do not necessarily mean a higher percentage of idling. If a short idle duration occurs at each stop, total idle time of that trip can be less than that of a trip with a longer idle duration at each stop and fewer total stops during the trip.

The strong correlation between kinetic intensity and stops per mile indicates that both metrics reflect some features of transient driving behavior.

Table 3: Correlations of All Cycle Metrics

	AspedWID	AspedWoID	PercID	Stops/Mi	VstdWID	VstdWoID	AveAcc	MaxAcc	AveDec	MaxDec	AeroV	CharAcc	KInt
AspedWID	1.00												
AspedWoID	**0.98**$^{+}$	1.00											
PercID	-0.83^{+}	-0.76^{+}	1.00										
Stops/Mi	-0.83^{+}	-0.82^{+}	**0.90**$^{+}$	1.00									
VstdWID	0.85^{+}	**0.90**$^{+}$	-0.69^{+}	-0.87^{+}	1.00								
VstdWoID	0.63^{+}	0.67^{+}	-0.54^{+}	-0.76^{+}	**0.91**$^{+}$	1.00							
AveAcc	-0.66^{+}	-0.60^{+}	0.79^{+}	0.82^{+}	-0.63^{+}	-0.57^{+}	1.00						
MaxAcc	-0.08	-0.18	-0.08	0.08	-0.12	0.09	-0.25	1.00					
AveDec	0.43^{+}	0.49^{+}	-0.30*	-0.29*	0.31*	-0.03	0.05	-0.74^{+}	1.00				
MaxDec	0.51^{+}	0.49^{+}	-0.41**	-0.33*	0.28*	0.00	-0.45^{+}	0.16	0.22	1.00			
AeroV	**0.94**$^{+}$	**0.97**$^{+}$	-0.73^{+}	-0.85^{+}	**0.97**$^{+}$	0.83^{+}	-0.65^{+}	-0.08	0.34*	0.40**	1.00		
CharAcc	**-0.93**$^{+}$	-0.89^{+}	0.88^{+}	0.89^{+}	-0.81^{+}	-0.63^{+}	0.79^{+}	-0.04	-0.28*	-0.47^{+}	-0.87^{+}	1.00	
KInt	-0.80^{+}	-0.80^{+}	0.82^{+}	**0.97**$^{+}$	-0.89^{+}	-0.81^{+}	0.73^{+}	0.07	-0.29*	-0.30*	-0.85^{+}	0.86^{+}	1.00

Note:

* Correlation is significant at the 0.05 level
** Correlation is significant at the 0.01 level
+ Correlation is significant at the 0.001 level

AspedWID: Average vehicle speed with idle
AspedWoID: Average vehicle speed without idle
PercID: Percentage idle
Stops/Mi: Stops per mile
VstdWoID: Standard deviation of vehicle speed without idle
VstdWID: Standard deviation of vehicle speed with idle
KInt: Kinetic intensity
MaxAcc: Maximum acceleration
AveDec: Average deceleration
MaxDec: Maximum deceleration
AeroV: Aerodynamic speed
CharAcc: Characteristic acceleration
AveAcc: Average acceleration

Certain redundant metrics were retained because they could be easily calculated from basic route information available to transit agencies. The retention of these cycle metrics results in collinearity. However, a potential predictive model does not necessarily have to include all selected cycle metrics as explanatory variables. After some collinearity was removed, the total number of metrics decreased from 13 to nine.

Further Dimensionality Reduction

It is evident from Table 3 that the four-cycle metrics, including average acceleration (AveAcc), maximum acceleration (MaxAcc), average deceleration (AveDec), and maximum deceleration (MaxDec), have weak correlations with the other metrics. To be useful for emissions modeling, they must correlate with emissions and fuel economy. Table 4 shows the correlations of these four metrics with emissions and fuel economy. Average acceleration shows moderate and significant correlations while maximum acceleration, average deceleration, and maximum deceleration do not correlate well with the emissions and fuel economy.

Table 4: Correlations of Four Cycle Metrics vs. Emissions and Fuel Economy

	CO_2	CO	HC	NOx	PM	FuelEco
AveAcc	0.84^+	0.81^+	0.79^+	0.84^+	0.77^+	-0.76^+
MaxAcc	0.02	0.18	0.05	-0.09	0.24	0.14
AveDec	-0.25	-0.33*	-0.31*	-0.18	-0.33*	0.15
MaxDec	-0.32*	-0.27*	-0.30*	-0.34*	-0.22	0.30*

Note:
* Correlation is significant at the 0.05 level
+ Correlation is significant at the 0.001 level

CO: Carbon monoxide
CO2: Carbon dioxide
HC: Hydrocarbon
NOx: Oxides of nitrogen
PM: Particulate matter
FuelEco: Fuel economy
AveAcc: Average acceleration
MaxAcc: Maximum acceleration
AveDec: Average deceleration
MaxDec: Maximum deceleration

The effects of average deceleration on the metrics are less than the corresponding effects of average acceleration because the correlations are low. The main reason is that during deceleration an engine is often at idle, so deceleration activities do not increase or decrease emissions and fuel consumption. However, when a vehicle accelerates, more fuel is consumed, producing more emissions (Wang et al. 2000). In addition, maximum acceleration and deceleration do not correlate with emissions and fuel economy, possibly because both metrics correspond to single points in a cycle. Based on the above analysis, average deceleration, maximum acceleration, and maximum deceleration were removed from further consideration.

Thus, through the initial correlation analysis of 13 cycle metrics, six metrics were determined to be useful for emissions and fuel economy modeling, and seven were removed because they were either redundant or appeared to have little correlation with emissions and fuel economy. The selected six-cycle metrics retained are average speed with idle, percentage idle, stops per mile, standard deviation of vehicle speed with idle, kinetic intensity, and average acceleration.

DETERMINATION OF ORDER OF IMPORTANCE OF THE SELECTED CYCLE METRICS

The following section focuses on the effects of the six chosen metrics and their order of importance in emission and fuel economy. Non-parametric correlation and stepwise regression analysis were performed to evaluate their effects.

Non-parametric Correlation Between Selected Cycle Metrics and Emissions and Fuel Economy

As previously mentioned, if a nonlinear relationship actually exists between paired variables, Pearson's correlation will underestimate it. For example, in this study, the Pearson's correlation between carbon dioxide and average speed is -0.78 with a coefficient of determination of 0.60. The two variables have a power decay relationship, and this relationship exhibits a much better fit (*R*-square of 0.91) than the linear fitting (*R*-square of 0.60). Considering this, the non-parametric statistical correlation, Spearman's correlation, was used to evaluate the relationship accurately. The Spearman's correlation (ρ) is a rank correlation of the data and it does not require variables to be normally distributed nor linear. The meaning and range of ρ are essentially the same as that of Pearson's correlation with a zero value representing no correlation, one or minus one indicating a perfect positive or negative fit, respectively. A ρ between a zero and one means increasing X corresponds to increasing Y and vice versa, and ρ between a zero and minus one means increasing X corresponds to decreasing Y and vice versa.

The Spearman's correlations between the six selected cycle metrics with emissions and fuel economy are in Table 5 together with their statistically significant levels. Average acceleration has the smallest correlation, making it the least important among the six selected metrics. Below is a detailed analysis for the importance of the other five metrics.

Table 5: Non-parametric Spearman's Correlation

	CO_2	CO	HC	NOx	PM	FuelEco
AspedWID	-0.9546	-0.965	-0.9208	-0.908	-0.9131	0.9558
PercID	0.9144	0.8674	0.8321	0.9172	0.8552	-0.9055
Stops/Mi	0.954	0.9665	0.9134	0.9033	0.9339	-0.9528
VstdWID	-0.8676	-0.8917	-0.8634	-0.8015	-0.8014	0.8729
AveAcc	0.6309	0.5441	0.5466	0.5833	0.5871	-0.6252
KInt	0.9537	0.9423	0.877	0.9032	0.9183	-0.9534

Note: All correlations are significant at the 0.0001 level ($p<0.0001$)

CO: Carbon monoxide
CO2: Carbon dioxide
HC: Hydrocarbon
NOx: Oxides of nitrogen
PM: Particulate matter
FuelEco: Fuel economy

AspedWID: Average vehicle speed with idle
PercID: Percentage idle
Stops/Mi: Stops per mile
VstdWID: Standard deviation of vehicle speed with idle
KInt: Kinetic intensity
AeroV: Aerodynamic speed

CharAcc:Characteristic acceleration
AveAcc: Average acceleration

Carbon Dioxide (CO_2) Emissions: The carbon dioxide emissions have the second strongest correlation with average speed with a coefficient of -0.9546, indicating that higher vehicle average speed results in lower carbon dioxide emissions. Actually, in addition to carbon dioxide, all other emissions have negative correlations with average speed. This shows that higher average speed produces lower emissions, which is consistent with previous findings (Wayne et al. 2007). Higher vehicle average speed involves fewer accelerations and decelerations, resulting in lower emissions. Stops per mile have the second largest correlation of 0.9540 followed by kinetic intensity with a correlation of 0.9537. Positive correlations imply that more stops per mile and higher kinetic intensity produce higher carbon dioxide emissions. Since the values of these three correlations are very close to each other, it is hard to tell which metric is most important for carbon dioxide emissions. Percentage idle and the standard deviation of vehicle speed have correlations of 0.9144 and -0.8676 with carbon dioxide emissions, respectively. The negative correlation shows that carbon dioxide emission decreases with increased standard deviation of vehicle speed. However, at the same average speed, increased standard deviation usually implies more transient cycle features, which produce higher carbon dioxide.

Carbon Monoxide (CO) Emissions: For carbon monoxide emissions, the variable stops per mile has the strongest positive correlation of 0.9665 with it, which is reasonable since carbon monoxide emissions in grams per mile are sensitive to the transient features of driving activities (Clark et al. 2002). The more stop-and-go features, the more deviations there are from a steady state, and the higher carbon monoxide emissions that are produced. Average speed has the second strongest correlation of -0.965 and kinetic intensity has a correlation of 0.942.

Hydrocarbon (HC) Emissions: Hydrocarbon emissions have the strongest correlation of 0.92 with average speed, followed by stops per mile of 0.91. The other correlations are below 0.9, indicating that stops per mile and average speed are the two most important metrics for hydrocarbon emissions.

Oxides of Nitrogen (NOx) Emissions: Oxides of nitrogen emissions show the strongest correlation with percentage idle, which is consistent with the fact that excessive idle could produce more of it (Clark et al. 2002). It is also noticed that average speed, stops per mile, and kinetic intensity have strong correlations of 0.9 and above with oxides of nitrogen, indicating their significance in this type of emissions.

Particulate Matter (PM) Emissions: Particulate matter shows the strongest correlation of 0.93 with stops per mile. Particulate matter is also highly correlated with carbon monoxide (0.9246), reinforcing that both are sensitive to the transient features of driving activities. In addition, particulate matter has strong correlations above 0.9 with average speed and kinetic intensity.

Fuel Economy: Fuel economy strongly correlates with average speed with a correlation coefficient of 0.9558, indicating the higher the average speed the lower the amount of fuel consumed. It does not mean this trend would be consistent at much higher average speed levels. Previous studies showed that fuel economy reaches a maximum at a specific vehicle speed and decreases at higher average speeds as aerodynamic drag begins to dominate. The result is a parabolic curve (Wayne et al. 2007, Rakha and Ding 2003).

The order of significance of the six-cycle metrics' impacts on emissions and fuel economy are in Table 6. Strong, moderate, and weak correlations are defined as coefficients higher than 0.9, between 0.8 and 0.9, and below 0.8, respectively. Stops per mile and average speed have strong correlations with all emissions and fuel economy. This result is consistent with the common interpretation that average speed reflects cruise features of driving activities while stops per mile are linked to transient features. Emissions and fuel economy might reflect the effects of both cruise and the transient features of driving cycles. However, it is difficult to tell which metric is most important, because those in the strong correlation category have very similar correlation coefficients.

Table 6: Summary of Order of Importance for the Selected Six Cycle Metrics

Dependent Variable	Strong Correlation	Moderate Correlation	Weak Correlation
CO	Stops/Mi, AspedWID, KInt	VstdWID, PercID	AveAcc
CO_2	Stops/Mi, AspedWID, PercID, KInt	VstdWID	AveAcc
HC	Stops/Mi, AspedWID	VstdWID, KInt, PercID	AveAcc
NOx	Stops/Mi, AspedWID, PercID, KInt	VstdWID	AveAcc
PM	Stops/Mi, AspedWID, KInt	VstdWID, PercID	AveAcc
FuelEco	PercID, AspedWID, Stops/Mi, KInt	VstdWID	AveAcc

Note: Strong Correlation: >=0.9; Moderate Correlation: >=0.8 & <0.9; Weak Correlation: <0.8

CO: Carbon monoxide
CO2: Carbon dioxide
HC: Hydrocarbon
NOx: Oxides of nitrogen
PM: Particulate matter
FuelEco: Fuel economy
AspedWID: Average vehicle speed with idle
PercID: Percentage idle
Stops/Mi: Stops per mile
VstdWID: Standard deviation of vehicle speed with idle
KInt: Kinetic intensity
AeroV: Aerodynamic speed
CharAcc: Characteristic acceleration
AveAcc: Average acceleration

Regression Analysis

To validate the significant effects of the selected cycle metrics on emissions and fuel economy, regression analyses were performed with selected metrics as independent variables. The regression models are expressed as in Equation (2) and their coefficients are in Table 7.

(2) $$y = a + \sum_{i=1}^{5} b_i x_i + \sum_{i=1}^{5} c_i x_i^2 + \varepsilon$$

where a is an intercept, b_i, and c_i are regression coefficients, ε is the residual term, and y is the dependent variables corresponding to emissions or fuel economy while x_i is the set of independent variables corresponding to the five selected cycle metrics in Table 6. Average acceleration was not considered due to its weak influence on the dependent variables. Squared terms for each of the selected cycle metrics were added to account for possible nonlinear relationships, and stepwise regression was employed to select the statistically significant variables to be used in the models.

Table 7: Regression Models Based on Selected Metrics

Term	CO_2	CO	HC	NOx	FuelEco	PM
Intercept	507.715	-0.017	0.193*+	3.236	6.730*+	-0.207*
AspedWID	15.492**	-	-	0.276*+	-0.046+	-
PercID	3268.232*+	-	0.138*+	46.742*+	-9.523*+	-
(PercID-0.268)*(PercID-0.268)	-6125.302*+	-	0.426*+	-	31.291*+	-
Stops/Mi	111.860**	0.673*+	-	0.286	-0.116	0.068*+
(Stops/Mi-5.20683)*(Stops/Mi-5.20683)	12.603*+	0.068*+	-	0.069*+	-0.017**	0.001**
VstdWID	17.135	-	-0.008*+	-0.132	0.060	0.014*
(VstdWID-12.8037)*(VstdWID-12.8037)	-11.253*+	-	0.001*+	-0.070**	0.021*+	-
KInt	73.522+	0.052	-	0.508*	-	-
(KInt-3.58075)*(KInt-3.58075)	-	-0.060+	-	-	-	-
Adjusted R^2	0.99	0.98	0.96	0.98	0.98	0.94
RMSE	86.15	0.52	0.01	1.07	0.22	0.07

Note:
* Significant at the 0.05 level
** Significant at the 0.01 level
+ Significant at the 0.001 level
*+ Significant at the 0.0001 level

RMSE: Root mean square error
CO: Carbon monoxide
CO2: Carbon dioxide
HC: Hydrocarbon
NOx: Oxides of nitrogen
PM: Particulate matter
FuelEco: Fuel economy
AspedWID: Average vehicle speed with idle
PercID: Percentage idle
Stops/Mi: Stops per mile
VstdWID: Standard deviation of vehicle speed with idle
KInt: Kinetic intensity
AeroV: Aerodynamic speed
CharAcc: Characteristic acceleration

The results were compared with regressions based on average speed as shown in Table 8. For each response variable, average speed-based power regressions give larger R-squared values and smaller root mean square errors (RMSE) compared to linear, polynomial, power, exponential, and logarithmic regressions. All R-squared values are greater than 0.85, except for 0.79 for oxides of nitrogen emissions, and the coefficients are statistically significant at the 0.0001 probability level ($p<0.0001$). Compared with the average speed-based regressions in Table 8, the regression results based on multiple metrics in Table 7 show adjusted R-squared values above 0.95, except the 0.94

for particulate matter, which is good considering the transient dependency of particulate matter emissions. Most of RMSE values are substantially reduced (over half), except that of particulate matter.

Table 8: Average Speed Based Regressions

Response	Regression	R^2	RMSE
CO_2	$y = 10021x^{-0.5343}$	0.91	306.74
CO	$y = 64.976x^{-1.147}$	0.94	1.18
HC	$y = 0.5402x^{-0.5258}$	0.86	0.02
NOx	$y = 66.8501x^{-0.4366}$	0.79	3.93
FuelEco	$y = x^{0.5298}$	0.91	0.60
PM	$y = 4.1171x^{-1.0262}$	0.90	0.10

Note:

RMSE: Root mean square error
CO: Carbon monoxide
CO2: Carbon dioxide
HC: Hydrocarbon
NOx: Oxides of nitrogen
PM: Particulate matter
FuelEco: Fuel economy

Figure 2 compares the estimated and experimental values of emissions and fuel economy for the NYBus cycle based on the old models (regressions based on average speed) and the new models (based on selected multiple cycle metrics). For the NYBus cycle, the new models show over 75% less percentage errors for all responses. Figure 3 compares the mean percentage errors (MPE) using both models after considering all cycle points. It shows that on average the new models have more than 40% reduction in MPE for carbon dioxide, hydrocarbons, and fuel economy. It also shows that carbon monoxide and particulate matter have MPE above 15% for both models, further indicating it is difficult to predict them due to their high sensitivity to transient features of vehicle operation. If interaction terms of the selected cycle metrics or the appropriate transformations (such as the Box-Cox method) of response variables were considered in the analysis, the multiple parameter models might show further improvement.

The regression models developed herein were used to determine the impact of cycle metrics on emissions and fuel economy. The intent of this analysis was to select cycle metrics for the development of a transit fleet emission model for use by transit agencies during vehicle procurement and strategic planning. Therefore, comparison and validation against existing average speed-based models are not presented here. An overview of the completed transit fleet emissions model and comparison of model results with the speed factor based EPA Mobile6 and MOVES models are presented in Wayne et al. (2011).

Figure 2: Comparison of Old and New Models to NYBus Cycle Estimation

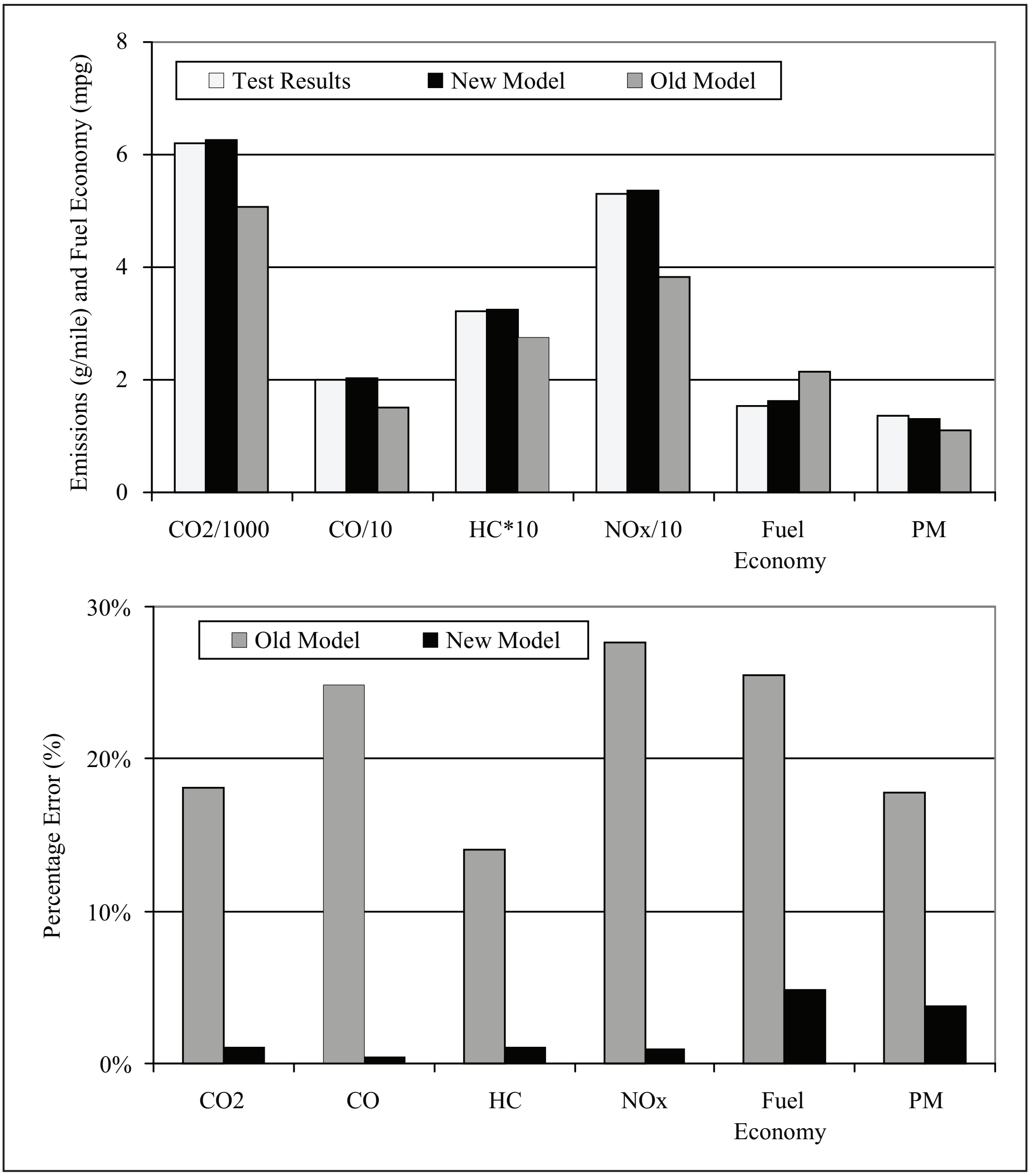
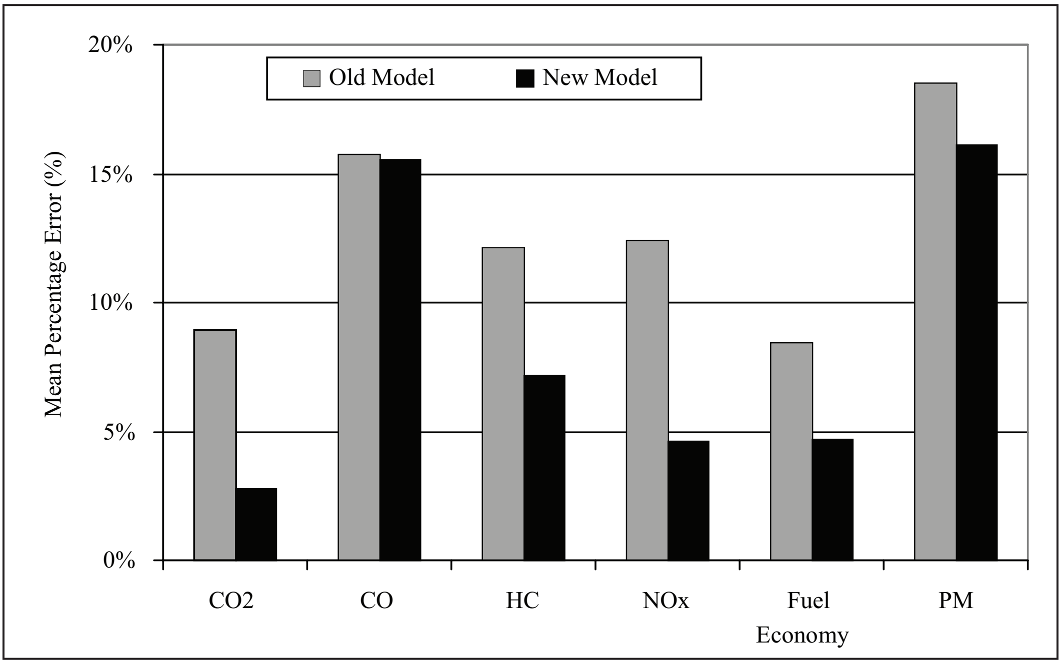


Figure 3: Mean Percentage Errors Comparison Between Old and New Models



CONCLUSION

A detailed correlation analysis was performed to investigate the relationships between duty cycle metrics and emissions and fuel economy and to identify the most important parameters for modeling. From an initial full correlation analysis of 13 cycle metrics, the number of metrics considered most useful for modeling was reduced to six. They are average speed with idle, percentage idle, stops per mile, standard deviation of vehicle speed, kinetic intensity, and average acceleration. Further analysis using non-parametric Spearman's correlations between the six selected cycle metrics with emission and fuel economy shows that average acceleration has the weakest correlation, implying that its ability to predict emissions and fuel economy is less significant. Results from the regression analysis show how adding selected cycle metrics to average speed (with idle) improves the regression models. The results of this study could assist in determining appropriate strategies for later IBIS development and implementation of a transit fleet model.

This study shows that duty cycles have significant impacts on emissions and the fuel economy of transit buses, and it provides a useful framework for the selection of the most influential cycle metrics for modeling. Beside average speed, other cycle metrics such as stops per mile, percentage idle, standard deviation of vehicle speed, and kinetic intensity were found to be important and could be used to predict emissions and fuel economy better. From a green environment and energy efficiency viewpoint, this study suggests that if drivers could operate their vehicles less aggressively, spend more time in cruise mode, have less stop-and-go patterns, or less idling behavior while parking, exhaust emissions and fuel consumption from the transportation sector could be reduced, and air quality and energy efficiency could be improved.

APPENDIX A

AeroV	Aerodynamic Speed
ART	Arterial Cycle
AspedWID	Average Vehicle Speed with Idle
AspedWoID	Average Vehicle Speed Without Idle
AveAcc	Average Acceleration
AveDec	Average Deceleration
Average Speed	Average Vehicle Speed with Idle
BEELINE	Westchester County NY Beeline Cycle
BRAUN	Braunschweig Cycle
CARB	California Air Resources Board
CBD	Central Business District Cycle
CFR	Code of Federal Regulations
CharAcc	Characteristic Acceleration
CNG	Compressed Natural Gas
CO	Carbon Monoxide
CO_2	Carbon Dioxide
COMM	Commuter Cycle
EMFAC	EMission FACtors Model
EPA	Environmental Protection Agency
ETC	European Transient Cycle
ETC_12	European Transient Cycle – Urban and Rural Segments
FTA	Federal Transit Administration
FuelEco	Fuel Economy
GVW	Gross Vehicle Weight
HC	Hydrocarbon
IBIS	Integrated Bus Information System
KInt	Kinetic Intensity
MAN	Manhattan Bus Cycle
MaxAcc	Maximum Acceleration
MaxDec	Maximum Deceleration
MOBILE6	Mobile Source Emission Factor Model
MOVES	Mobile Vehicle Emission Simulator
mph	Miles per Hour
MY	Model Year
NOx	Oxides of Nitrogen
NYBUS	New York Bus Cycle
NY-COMP	New York Composite Cycle
OCTA	Orange County Transit Authority Cycle
PercID	Percentage Idle
PM	Particulate Matter

Stops/Mi	Number of Stops per Mile
Stops/mile	Number of Stops per Mile
TransLab	Transportable Heavy-Duty Vehicle Emission Laboratory
UDDS	Urban Dynamometer Driving Schedule
VMY	Vehicle Model Year
VstdWID	Standard Deviation of Vehicle Speed with Idle
VstdWoID	Standard Deviation of Vehicle Speed without Idle
WMATA	Washington Metropolitan Area Transit Authority

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Gate Violations by Truck Drivers at Highway-Rail Grade Crossings in Two Cities

by Aemal Khattak

Gate violations during train crossing events by truck drivers at highway-rail grade crossings in two cities were investigated. About 22% of the collected observations involved gate violations by truck drivers. Analysis showed that the frequencies of gate violations increased with higher truck traffic during crossing events and drivers of single-unit trucks displayed a greater propensity for gate violations compared with drivers of trucks with trailers. Violations were more frequent with longer times between the onset of flashing lights and train arrivals at the crossings. Options for reducing truck drivers' gate violations at gated crossings are provided.

INTRODUCTION

The objective of this research was to investigate gate violations by truck drivers at dual-quadrant gated highway-rail grade crossings (HRGCs) in two cities. Dual-quadrant gated HRGCs have gates in only two of the four quadrants, i.e., gates on both sides of the road only extend out to the middle of the road. As such, motorists can illegally pass around fully-deployed gates. HRGCs serve as junctions for multiple transport modes on the surface transportation network and they are conflict points between rail and highway traffic. For 2010, the Federal Railroad Administration (FRA) reported 2,107 incidents at HRGCs and a rate of 2.85 HRGC incidents per million train miles (USDOT 2012). These incidents involved 256 fatalities and 854 non-fatal injuries. Trucks and trucks with trailers were involved in 386 incidents, resulting in 24 fatalities and 233 non-fatal injuries. At HRGCs, train consists (units) transporting hazardous materials were involved in 47 crashes while 14 involved trucks carrying hazardous materials that required the evacuation of 471 people. Hazardous materials are frequently transported by both rail and trucks, and the implications of truck-train crashes at HRGCs are potentially more ominous compared with other highway crashes.

The issue of collisions between trucks and trains is important because of the relatively high severity of such crashes and environmental concerns arising from possible spillage of hazardous materials. Given that rail and truck traffic in the US is expected to grow, it is prudent to investigate truck-train safety at HRGCs; the ultimate goal being improvement of public safety.

This research was carried out in Nebraska where the law prohibits drivers from driving through, around or under any rail crossing gate or barrier while the gate or barrier is closed or is being opened or closed (Neb. Rev. Stat. 60-6,170, 2009). Many other states across the U.S., e.g., Missouri, New Hampshire, North Dakota, and Rhode Island have similar laws. The penalty for a first violation in Nebraska disqualifies a commercial motor vehicle driver for a period not less than 60 days. A second violation disqualifies a driver for not less than 120 days during any three-year period for separate incidents while a third violation during any three-year period for separate incidents disqualifies a commercial motor vehicle driver for a period not less than one year.

The research methodology consisted of collecting data at two dual-quadrant gated Nebraska HRGCs where truck drivers were observed during train crossing events along with other pertinent factors. The collected data were then statistically analyzed to assess the prevalence of gate violations by truck drivers. The organization of the remaining paper is as follows. A review of relevant literature follows this introduction, which is ensued by a description of data collection. The next section presents data analysis including a Poisson model of truck drivers' gate violations at the two HRGCs.

The paper ends with research conclusions and a discussion of possible options for both practitioners and researchers to improve truck drivers' safety at HRGCs.

LITERATURE REVIEW

Although not all violations by truck drivers at HRGCs result in crashes, the prevalence of such maneuvers at crossings is an indication of its safety. According to Council et al. (1980) gate violations were an appropriate surrogate measure of crashes. Similarly, a study by Abraham et al. (1998) indicated promise for the use of violation data in determining the relative hazardousness of rail-highway crossings in combination with crash histories. Overall, the use of violations to study HRGC safety is well-established; examples include Carlson and Fitzpatrick (1999), Hellman et al. (2007), Khattak (2007), Khattak and McKnight (2008), Khattak (2009), and Khattak and Luo (2011).

Davey et al. (2007) interviewed truck drivers as well as train drivers regarding their experiences and perceptions of dangers at HRGCs in Australia. The configuration of at-grade crossings was found to affect heavy vehicle drivers' visibility and effective vehicle clearance. With regard to behavior, willful violation of crossing protocols, often as a time-saving measure, as well as truck drivers' complacency due to high levels of familiarity were cited.

Heathington et al. (1990) investigated warning time needs at HRGCs and reported warning times in excess of 30-40 seconds caused many more drivers to engage in risky crossing behaviors. Most drivers expected trains to arrive within 20 seconds from the moment when the traffic control devices were activated. Drivers lost confidence in traffic control systems if warning times exceeded 40 seconds at crossings with flashing light signals and 60 seconds at gated crossings. Abraham et al. (1998) reported that the timely arrival of trains after the warning devices were triggered was an essential element that motorists assessed when taking risks.

Rys et al. (2009) evaluated the use of stop signs at passive grade crossings. Their results showed that a majority (79%) of drivers did not stop at installed stop signs and that drivers of heavy trucks had a lower level of compliance than other types of vehicles. Finally, Yeh and Multer (2008) provided a comprehensive review of research on motor vehicle drivers' behavior at HRGCs; this document was an update to an earlier report by Lerner et al. (1990).

In summary, the study of violations at HRGCs provides useful information on the safety of HRGCs. Research on truck drivers' behavior at HRGCs, while sparse, indicated that violations were for saving travel times and due to complacency resulting from high levels of crossing familiarity. Excessively long warning times at HRGCs encouraged risky behavior by motor vehicle drivers. The reviewed literature did not reveal publications specifically dealing with the frequency and characteristics of gate violations by truck drivers at HRGCs. The next section describes the data collection effort.

DATA COLLECTION

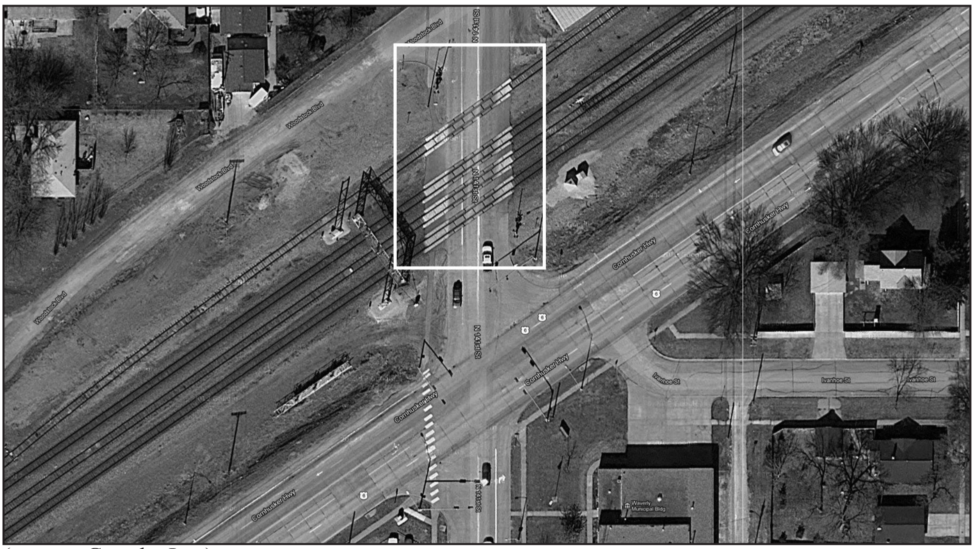
Data collection consisted of focusing on different types of gate violations (according to Nebraska law) by truck drivers at two dual-quadrant gated HRGCs. Drivers of both single unit (SU) trucks and trucks with trailers were included in this research. The following three gate violations were taken into account.

1. Trucks passing under descending HRGC gates (V1),
2. Trucks passing around fully lowered HRGC gates (V2), and
3. Trucks passing under ascending HRGC gates (V3).

An observation consisted of an event with flashing gate lights and trucks at the HRGCs with opportunities for gate violations (e.g., observations with trucks not at the front of the waiting queue were ignored). Video footage was continuously recorded at the North 141st Street grade crossing in

Waverly and at the M Street crossing in Fremont, both located in Nebraska. The Waverly HRGC (USDOT crossing no. 074940T) comprised four sets of rail tracks crossing two lanes of roadway and protected by dual-quadrant gates. The estimated average annual daily traffic (AADT) at this HRGC was 2,630 vehicles with 2% trucks. The Fremont crossing (USDOT crossing 074662E) consisted of two sets of tracks crossing two lanes of a roadway and protected by dual-quadrant gates. The estimated AADT at the Fremont HRGC was 1,315 vehicles with 4% trucks. Both crossings afforded clear sight distances in all directions and were equipped with flashing lights, crossbuck signs, and audible bells. Figures 1 and 2 show the study sites. Day- and night-vision cameras and digital video recorders (DVR) were used to record train crossing events. Instances with trucks present with opportunities for gate violations at the crossings were extracted from the video footage and subsequently used for pertinent data extraction to a spreadsheet.

Figure 1: HRGC at the North 141st Street in Waverly, Nebraska



(source: Google, Inc.)

Figure 2: HRGC at the M Street Crossing in Fremont, Nebraska

(source: Google, Inc.)

Sixteen variables representing different types of gate violations by truck drivers, counts of SU trucks and trucks with trailers, train traffic, temporal features, and environmental and pavement surface characteristics at the time of train crossings were recorded for each observation. Table 1 presents a list of those variables along with relevant coding information. A total of 476 observations were collected as part of the dataset.

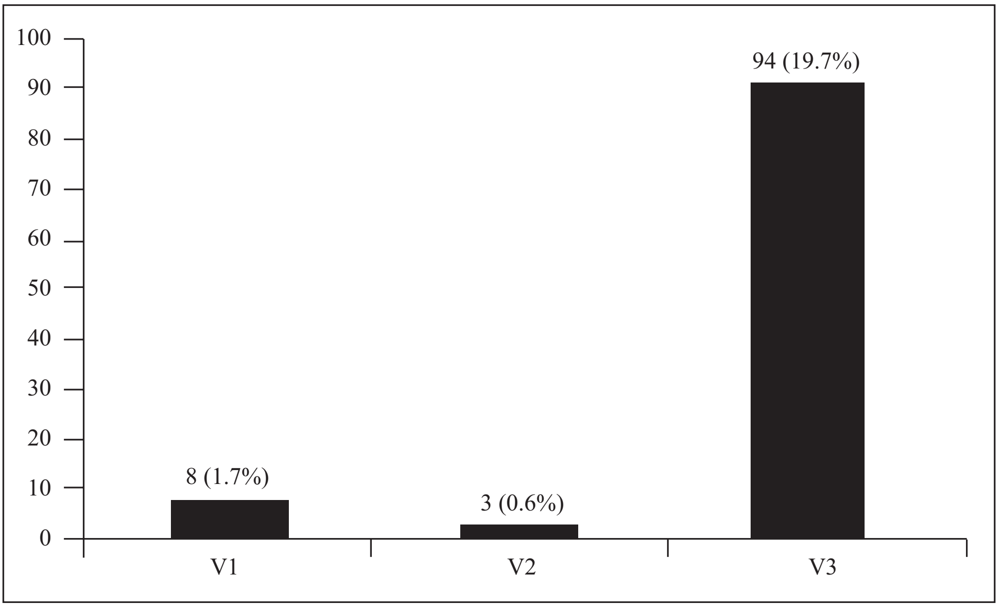
Table 1: Collected Variables

Variable	Description	Coding/Units
Su_V1	Number of SU trucks passing under descending gates during an observation	0, 1, 2, …
Su_V2	Number of SU trucks passing around fully lowered gates during an observation	0, 1, 2, …
Su_V3	Number of SU trucks passing under ascending gates during an observation	0, 1, 2, …
Ttrlr_V1	Number of trailer trucks passing under descending gates during an observation	0, 1, 2, …
Ttrlr_V2	Number of trailer trucks passing around fully lowered gates during an observation	0, 1, 2, …
Ttrlr_V3	Number of trailer trucks passing under ascending gates during an observation	0, 1, 2, …
N_Sutrks	Count of SU trucks during an observation	1, 2, …
N_Trktrlr	Count of trailer trucks during an observation	1, 2, …
N_Trains	Number of passing trains during an observation	1, 2, …
T_Stop	Indicator variable for train stoppage on the HRGC	1 if stopped, 0 otherwise
G_Down	Elapsed time from start to end of flashing lights	Seconds
T_Arrival	Elapsed time between onset of flashing lights and train arrival at the crossing	Seconds
Day	Day of week of the observation	1 if Mon, 2 if Tue, ..., 7 if Sun
Daytime	Light condition	0 if nighttime, 1 if daytime, 2 if dawn or dusk
Weather	Weather condition	0 if clear, 1 if rain, 2 if snowing, 3 if foggy, 4 if other
Pavement	Pavement surface condition	0 if dry, 1 if wet, 2 if snow on pavement

DATA ANALYSIS

Zero gate violations by truck drivers were observed in 78.2% of the 476 observations, a single gate violation was observed in 21.6% of those observations, while 0.2% observations constituted two gate violations by different truck drivers. Figure 3 shows the frequency of different types of gate violations observed; the most frequent violation type was passing under ascending gates after passage of the train. On average, truck drivers were involved in 0.22 gate violations per crossing event with a standard deviation of 0.42 violations (variance = 0.17 violations^2).

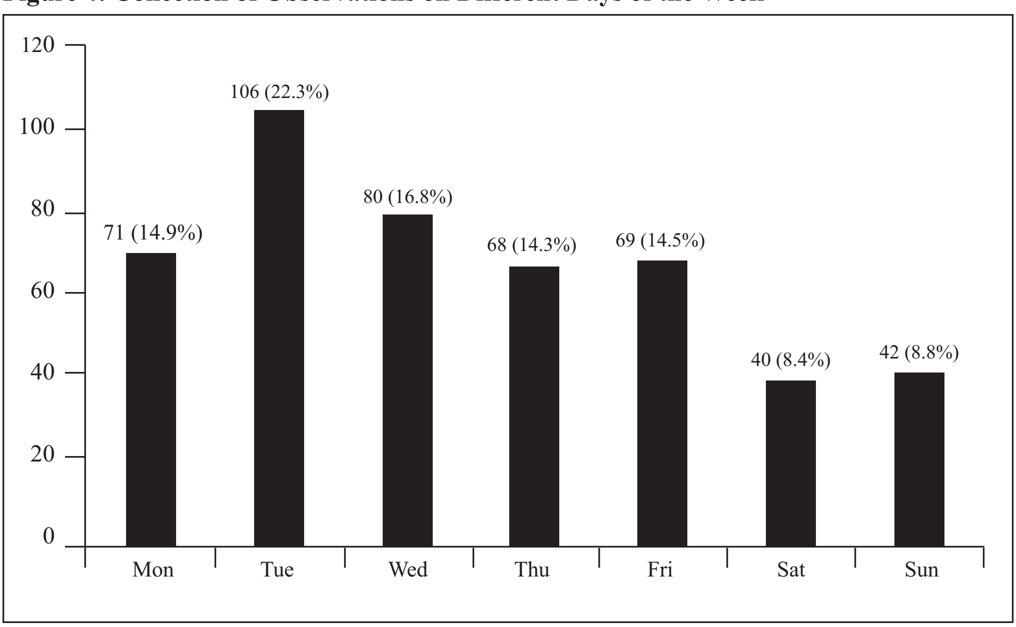
Figure 3: Frequency of Different Types of HRGC Gate Violations by Truck Drivers



During data collection, 337 SU trucks and 147 trucks with trailers were observed at the two HRGCs. The number of trains observed during data collection was 544, of which 92 (16.9%) stopped on the HRGCs. The average gate closure time of a crossing event was 363.5 seconds (about six minutes) while the average time between the onset of flashing lights and train arrival at the crossing was 46.1 seconds. Provision of 20 seconds as a minimum interval between the onset of warning devices and train arrival at the crossing is mandated.

Figure 4 shows the distribution of observations on different days of the week. Fewer observations were collected on Saturday and Sunday compared with week days. Figure 5 presents the distribution

Figure 4: Collection of Observations on Different Days of the Week



of observations across different times of the day. The majority (81.7%) of the observations were collected during daytime while somewhat equal observations were collected under dawn or dusk and nighttime conditions.

Figure 5: Time of Day Distribution of Observations

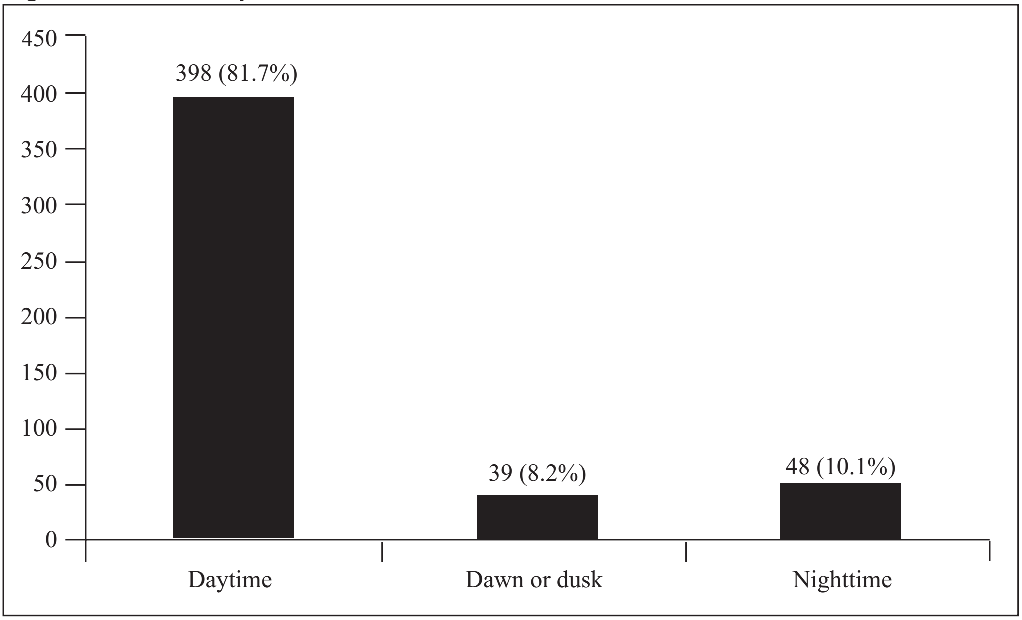


Figure 6 presents the distribution of observations in different weather conditions; the majority of observations were collected in clear weather. Figure 7 presents pavement surface conditions observed during crossing events. About 8% of the observations each were on wet and snow on pavement conditions. Moisture and snow on the pavement can stay for relatively long periods and therefore the number of collected observations under these two pavement surface conditions was larger than those collected when it was raining or snowing (Figure 6). An account of Poisson modeling of gate violations by truck drivers at HRGCs follows.

The Poisson Model

Aggregate counts of gate violations by truck drivers at HRGCs during crossing events were modeled using the Poisson distribution. This variable was obtained by aggregating the three different types of gate violations for both drivers of trucks with trailers and drivers of SU trucks (Su_V1 + Su_V2 + Su_V3 + Ttrlr_V1 + Ttrlr_V2 + Ttrlr_V3). The aggregation was necessitated as several violation categories in the collected data were sparse and did not provide meaningful results when analyzed separately.

The benchmark model for count data is the Poisson distribution (Cameron and Trivedi 1998). The Poisson model is appropriate for analysis of count data consisting of nonnegative integer values and when the mean and variance of the count variable are not significantly different from each other (as was the case with the dataset under analysis). According to Washington et al. (2011), the probability of a crossing event *i* having y_i gate violations (where $y_i \geq 0$), is given by:

(1) $$P(y_i) = (e^{-\lambda_i} \lambda_i^{y_i}) / (y_i!)$$

Figure 6: Observations in Different Weather Conditions

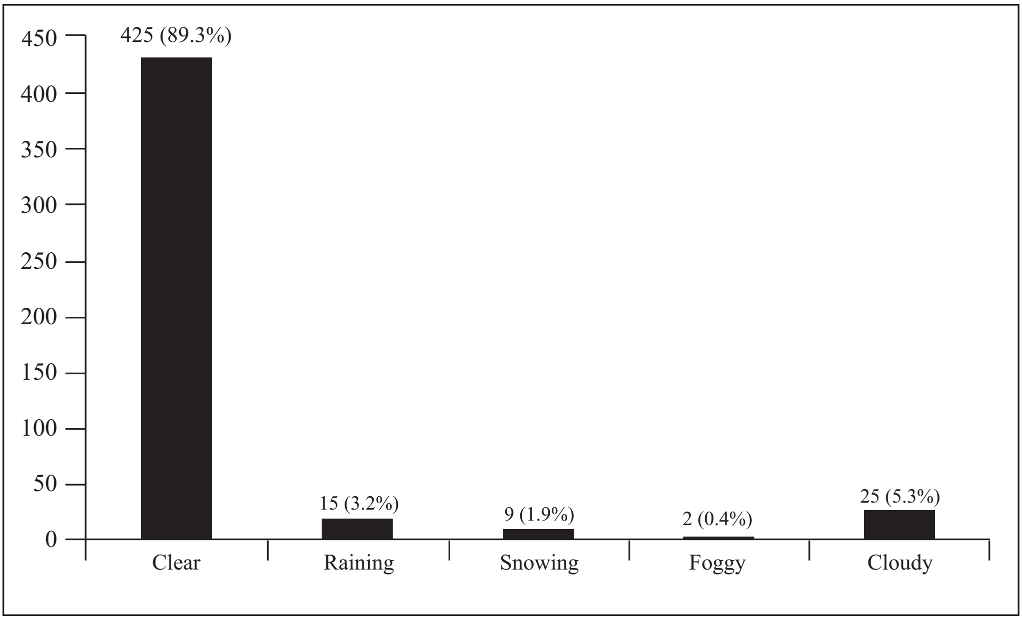
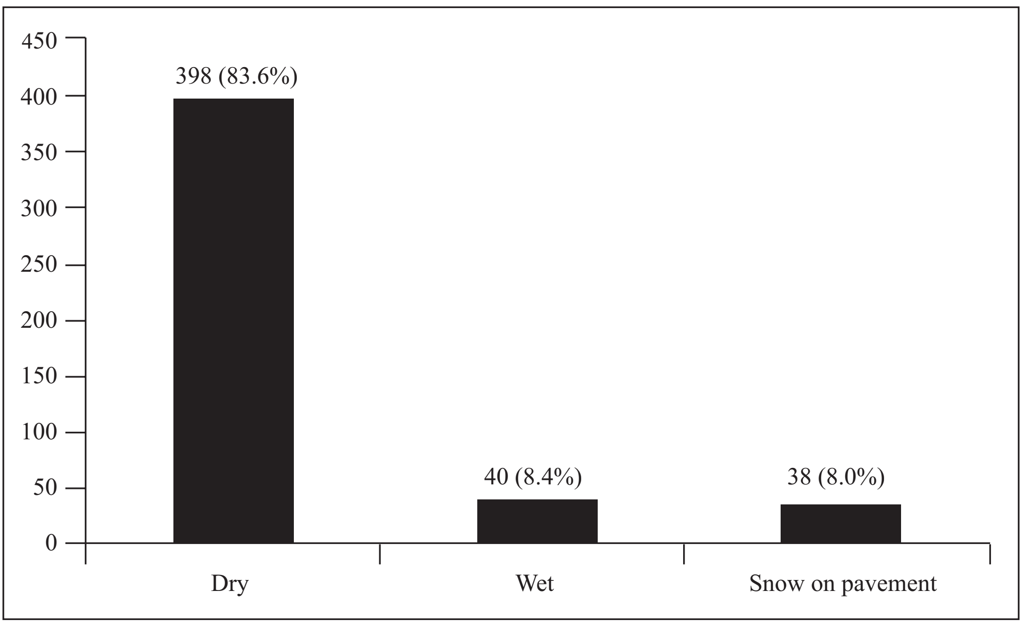


Figure 7: Observations Under Different Pavement Surface Conditions



Where $P(y_i)$ is the probability of crossing event i having y_i gate violations, e is the base of the natural logarithm, and λ_i is the Poisson parameter for crossing event i, which is equal to crossing event i's expected number of gate violations, $E[y_i]$. $y_i!$ represents the factorial of y_i.

Poisson models are estimated by specifying the Poisson parameter λ_i as a function of independent variables. The most common relationship between independent variables and the Poisson parameter is the log-linear model:

$$(2)\quad \lambda_i = e^{\beta X_i}$$

Where X_i is a vector of independent variables for crossing event i and β is a vector of estimable parameters. This model is estimable by standard maximum likelihood methods with the logarithm of the likelihood function given as:

$$(3)\quad LL(\beta) = \sum_{i=1}^{n} \left[-e^{\beta X_i} + y_i \beta X_i - Ln\,(y_i!) \right]$$

Marginal effects (evaluated at mean values) are used to determine the effects of the independent variables on the dependent variable; they provide an estimate of the impact of a unit change in the variable on the expected frequency of the count variable. Alternatively, elasticity can be computed to assess the effect of a 1% change in the independent variable on the expected frequency of λ_i.

The likelihood ratio test is used to assess competing models, usually a full or complete model over another competing model that is restricted by having a reduced number of model parameters. The likelihood ratio test statistic is:

$$(4)\quad X^2 = -2\left[LL(\beta_R) - LL(\beta_U) \right]$$

Where $LL(\beta_R)$ is the log-likelihood at convergence of the restricted model, considered to have all parameters in β equal to 0 or just to include the constant term, and $LL(\beta_U)$ is the log-likelihood at convergence of the unrestricted model. The X^2 statistic is chi-squared distributed with the degrees of freedom equal to the difference in the number of parameters in the restricted and unrestricted model. A measure of overall model fit is the ρ^2 statistics given as:

$$(5)\quad \rho^2 = 1 - \frac{LL(\beta)}{LL(0)}$$

Where $LL(\beta)$ is the log likelihood at convergence with parameter vector β and $LL(0)$ is the initial log likelihood with all parameters set to zero. The value of ρ^2 varies between 0 and 1 and values closer to 1 indicate a better fitting model compared to values closer to 0. The estimated Poisson model for frequency of truck drivers' gate violations is presented next.

Modeling Truck Drivers' Gate Violations

Table 2 shows the estimated Poisson model for counts of truck drivers' gate violations with relevant summary statistics; the model equation is:

$$(6)\ \lambda = e^{0.699*N\_Sutrks+0.563*N\_Trktrlr+0.003*T\_Arrival+0.506*Night-1.253*Rain-0.789*Snow\_Pvt-2.366}$$

A positive estimated coefficient shows that the frequency of gate violations by truck drivers increases with increasing values of the variable while a negative estimated coefficient indicates that gate violations decrease with increasing values of the variable. Estimated coefficients in the model were statistically tested using a student's t-test to assess if they were different than zero at 95% or 90% confidence levels. Absolute t-statistic values of 1.96 or greater or 1.64 or greater indicate statistical significance at the 95% or 90% confidence levels, respectively. Alternatively, Table 2 provides p-values for the estimated coefficients; a p-value is the probability of obtaining a test statistic at least as extreme as the one that was observed/estimated. Values of 0.05 and 0.01 are thresholds for statistical significance at 95% and 90% confidence, respectively.

Table 2: Estimated Model for Counts of Gate Violations by Truck Drivers at HRGCs

Variable	Description	Estimated Coefficient	t-Statistic	P-Value	Marginal Value	Mean
N_Sutrks	Count of SU trucks during an observation	0.699	3.296	0.001	0.155	0.706
N_Trktrlr	Count of trailer trucks during an observation	0.563	2.221	0.026	0.125	0.308
T_Arrival	Elapsed time between onset of flashing lights and train arrival (sec)	0.003	1.968	0.049	0.001	46.105
Night	Indicator variable for nighttime	0.506	1.850	0.064	0.112	0.101
Rain	Indicator variable for rain	-1.253	-1.315	0.188	-0.278	0.031
Snow_Pvt	Indicator variable for snow on pavement	-0.789	-1.543	0.122	-0.175	0.080
Constant	Constant in the model	-2.366	-8.547	0.000	-0.525	-

Model summary statistics	
Number of observations	473
Log likelihood	-254.292
Restricted Log likelihood	-263.732
P^2	0.036
X^2 (with 6 degrees of freedom)	18.879
P-value	0.004

Two variables indicating counts of SU trucks (N_Sutrks) and trucks with trailers (N_Trktrlr) were included in the model specification. When added, they represent truck traffic with opportunities for gate violations; in other words, truck drivers' exposure to gate violations where exposure was the state of being exposed to involvement in gate violations. Both variables were statistically significant at the 95% confidence level, indicating that gate violations increased with greater numbers of SU trucks and trucks with trailers arriving at HRGCs. The marginal value for SU trucks showed that for each additional SU truck (beyond its mean value and with other independent variables held constant at their respective mean values), gate violations increased by 0.155 violations per crossing event. Also, the larger marginal value of SU trucks (0.155) compared with the marginal value for trucks with trailers (0.125) indicated that SU truck drivers had a comparatively higher propensity for gate violations. This may be explained by the relatively smaller dimensions and shorter acceleration times associated with SU trucks compared with trucks with trailers.

The variable T_Arrival represented the elapsed time between the onset of flashing lights and train arrivals at the crossings. The estimated coefficient for this variable was positive and statistically significant at the 95% confidence level showing that greater values of T_Arrival were associated with more frequent gate violations by truck drivers. The model specification included an indicator variable for nighttime (Night =1 if nighttime). The estimated coefficient for this variable was positive and statistically significant at the 90% confidence level (t-statistic >1.64). Thus, nighttime was associated with higher frequency of gate violations compared with other times; its marginal value showed that an additional 0.112 gate violations per crossing event occurred during nighttime.

Finally, two indicator variables for rain (Rain=1 if raining) and snow on pavement (Snow_Pvt=1 if snow on the pavement) were included in the model to explore the effects of adverse weather and pavement surface condition on gate violations by truck drivers. The estimated coefficients in both cases were negative (indicating a reduction in gate violations) but statistically not significant at the 90% confidence level. Therefore, the collected data did not provide enough evidence regarding statistically significant relationships between frequencies of truck drivers' HRGC gate violations and rain and truck drivers' HRGC gate violations and presence of snow on pavement. The two variables, however, were retained in the model for demonstration.

Other variables available in the database were tried in the model specification but found statistically not significant. These included: elapsed time from start to end of flashing lights, the number of passing trains, train stoppage on the HRGC, an indicator variable for weekends, and an indicator variable for crossing location (Waverly or Fremont). These variables were excluded from the model specification for parsimony. Additionally, the estimated Poisson model was statistically tested for overdispersion (i.e., when the variance of the dependent variable is significantly larger than its mean) and no such evidence was detected. Conclusions and a discussion of options for reducing truck drivers' gate violations at gated crossings, including the research limitations, are presented next.

CONCLUSIONS AND DISCUSSION

This research explored gate violations by truck drivers at dual-quadrant gated HRGCs that were located in two different cities. Three different types of violations were observed during data collection: trucks passing under descending HRGC gates, trucks passing around fully lowered HRGC gates, and trucks passing under ascending HRGC gates. These three types of violations were aggregated and about 22% of the total observations involved gate violations by truck drivers. Based on the Poisson model results, the following conclusions were reached.

- At dual-quadrant HRGCs located in cities, the frequencies of gate violations by truck drivers increased with higher exposure of truck drivers.
- The propensity of SU truck drivers for gate violations at dual-quadrant HRGCs located in cities was higher compared with drivers of trucks with trailers.
- Longer times between the onset of flashing lights and train arrivals at dual-quadrant HRGCs located in cities contributed to higher frequencies of gate violations by truck drivers.
- Nighttime was associated with greater frequencies of gate violations by truck drivers at dual-quadrant HRGCs located in cities.

The conclusions are relevant to isolated dual-quadrant HRGCs located in cities and do not pertain to four-quadrant gated HRGCs or those located in corridors/rural areas. An aspect of these conclusions, pertinent to practitioners and practice-ready, is reducing truck traffic at HRGCs to limit drivers' exposure to gate violations. In a city environment, this may be feasible by restricting or prohibiting truck traffic at HRGCs where proximate grade-separated crossings are available. Another practical aspect is that of differentiated truck drivers' education. While all truck drivers should be the focus of education on the dangers of HRGC gate violations, the HRGC safety issue should be especially emphasized to drivers of SU trucks due to their higher propensity for involvement in gate violations. Such emphasis may be achieved via revisions to existing publications such as the Operation Lifesaver's Highway-Rail Grade Crossing Training for Professional Truck Drivers.

Longer elapsed times between the onset of warning devices and arrival of trains at crossings located in cities encourages drivers' disregard for traffic signs and signals. This issue was highlighted by Heathington et al. (1990) and by Abraham et al. (1998), though not specifically in the context of truck drivers. In the case of truck drivers, the issue of HRGC gate violations may be exacerbated by the need to deliver just-in-time deliverables and truck drivers' mileage-based remuneration. The research reported herein underscores the need to check excessively large warning times at dual-quadrant HRGCs located in cities beyond the minimum required time of 20 seconds. This aspect can be addressed by researchers and practitioners together. Research on reliable train detection, its speed and acceleration/deceleration estimation, and development of new algorithms for gate timing and highway traffic signal preemption (if involved) is needed. Practitioners would need to implement the outcomes of such research at city-based HRGCs to reduce elapsed times between the onset of warning devices and arrival of trains at crossings. However, in rural rail corridors with higher train speed limits, lengthening of warning times may be desirable under certain circumstances. Appropriate warning times at HRGCs depend on crossing and train characteristics and caution must be exercised in changing warning times at HRGCs.

Ways to reduce gate violations at nighttime by truck drivers are needed. Besides education, a possible practical option to reduce nighttime gate violations is stronger enforcement of motor vehicle laws at HRGCs at nighttime. Penalties for gate violations in Nebraska and some other states appear sufficiently stringent to quickly deter truck drivers from engaging in risky maneuvers at HRGCs.

Research Limitations

Limitations of the research presented herein include collection of data at only dual-quadrant HRGCs located in two cities, narrow geographic coverage, and lack of data on truck drivers' characteristics (age, driving experience, etc.). Therefore, the generalization of the findings is limited and studies involving multiple HRGCs with wider geographic coverage, including rural HRGCs in corridors and studies that collect data on drivers besides HRGC gate violations, are recommended. While this research did not uncover significant evidence regarding weather and pavement surface condition effects on HRGC safety, these two factors warrant further investigation by researchers. Finally, reduction of violations depends on strict enforcement, driver education, and recurrent training of truck drivers and consolidated efforts are needed to improve safety at HRGCs.

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Book Reviews

Spiegelman, Clifford H., Park, Eun Sug, and Rilettt, Laurence R. Transportation Statistics and Microsimulation. *Boca Raton, London, New York: CRC Press, 2010. ISBN 9781439800232.*

Transportation Statistics and Microsimulation

by Sunanda Dissanayake

While transportation engineers and especially graduate students in transportation engineering use statistics for various purposes, their general level of understanding seems to be lacking in many situations. Even though a majority of engineering graduates have taken some type of a statistics course during their undergraduate course of study, such courses are typically taught by faculty members in statistics or mathematics and lack the practical applications that are common in transportation engineering. On the other hand, graduate level statistics courses offered by statistics or mathematics departments are too theoretical and do not offer much assistance to graduate students in transportation engineering. With this background, there has been a need for textbooks covering practical statistical applications in transportation-related topics for a long time, and this book seems to be addressing that need.

The first several chapters of the book (2-5), which consists of 15 chapters, cover the background details, such as standard probability and statistical techniques, that are needed to follow the more advanced sections in the rest of the book. They cover such topics as basics of graphical methods, numerical summary methods, random variables, probability mass functions, and common probability distributions and provide easy-to-follow examples from various applications of transportation such as speed measurements, traffic volume data, pedestrian arrivals, and driving under influence situations.

The next several chapters (6-9) cover statistical inferences or what is commonly known as hypothesis testing for single and multiple variables as well as continuous and categorical data. A commonly used statistical modeling technique, regression, is discussed in the next chapters (10-11), where the authors discuss simple linear regression, multiple linear regression, and generalized linear models. Simple and multiple linear regressions are typically used in transportation applications to predict a certain continuous variable as a function of a number of independent variables, whether they are continuous or discrete. However, when it comes to predicting dependent variables of a discrete nature, alternative approaches need to be sought, and the authors provide the details of Poisson and negative binomial regression models to serve that purpose. Both these methodologies have common applications in safety analysis, especially in modeling crash frequency among many other transportation-related areas.

More advanced concepts such as experimental design, uncertainty estimation, and Bayesian estimation are discussed in Chapters 12-14, where the authors do a commendable task of transforming these more advanced topics into a simple, easy to understand format. Finally, in the last chapter, transportation microsimulation models that are becoming more common for modeling large-scale traffic and planning studies are described, which could be used by more advanced and creative students.

A number of transportation statistics related examples are provided throughout the book so that more hands-on experience could be gained by actually working on the example problems. The data for some examples are, however, available at a website for downloading. While this may not create any critical challenges in most situations, it would be more helpful if the data could be made available in the book itself either in print format, in an appendix, or in a CD/DVD that comes with the book, so that everything could be self-contained. Even though many concepts in statistics are learned by manual methods, in practice many users prefer to use statistical packages, which reduce the time consuming nature of the calculations. Accordingly, it makes perfect sense for the authors to have adopted a software package (JMP by SAS) to do the problem solving. While the authors justify the selection of this specific package on the basis of its strong graphics capabilities, this selection could be turning away some of the students or courses that follow other popular software packages. Nonetheless, while it is much easier to use the authors' choice of software package if one is using their textbook, one can still apply alternative packages to the concepts presented in the book.

All in all, this textbook fulfills a need in the area of transportation statistics by providing basic concepts via an easy to follow format and practical examples.

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Button, Kenneth. Transport Economics*, 3rd ed. Cheltenhaum, UK and Northampton, MA: Edward Elgar, 2010. ISBN 978 1 84064 191 2 (paperback)..*

Transport Economics

by Wesley W. Wilson

Economic well-being is driven by trade, and transportation drives trade. Despite this linkage, interest in transportation has waned. Relatively few university economics departments offer courses in transportation as part of their curriculum; there are relatively few books in the area; and relatively little work is published in general economics journals. *Transport Economics*, by Kenneth Button is the most current and up to date book in the field. It is in its third edition, with the first edition published in 1982, and the second in 1996. It has 14 chapters and 498 pages that cover the venerable history of transport economics, identifies the contributions of major ”thinkers” in the field, along with the foundation that is in most books on the subject (demand, costs, congestion, investment). In addition, however, there are specialized chapters that explicitly deal with environmental issues, logistics, planning, and forecasting. The inclusion of these chapters hit on emerging issues and connections to other fields. A thorough read of the text will give readers a strong sense of the history of the field, central figures, but also important developments and linkages to other fields that reflect the multidisciplinary nature of the field of transportation.

The first three chapters give an excellent overview of the field, its history, its magnitude and emerging trends and issues. The first chapter points out some of the challenges of transport as a profession. I very much appreciate the discussion of the importance of transportation to economics which is then followed by the fact that there are very few specialists in the field. This is, indeed, a fact that has plagued the field for the last several decades. He notes that there are a number of people that dabble in the field, and this dabbling has led to major innovations in economics. These include the role of common and joint costs that came from the famous Pigou-Taussig debates in the early 1900s, the random utility model from Dan McFadden in the 1970s, congestion and peak load pricing, and a wide array of studies that examine the level and structure of costs, efficiency, demand, the pricing of public goods, the impetus and effects of government involvement in business, etc. There are many references to hallowed names in economics and their contributions to transportation. Button appropriately notes that "…many of the seminal papers on the subject [transportation] that have appeared in the general economics literature have often been produced by individuals with a broad interest in economics rather than transport specialists." (p. 6).

Chapter 2 is a broad overview that is filled with facts and figures. Many books have such information, and I do believe it is an important feature; it gives students a sense of the sheer magnitude that transportation plays in their own lives as well as the local, national, and world economies. Chapter 3 begins with a discourse on the desire for transportation, and points quite rightly, that transportation is not consumed for pleasure but for what transportation allows you to consume. I very much appreciated the sections that cover industrial location decisions and the market area of firms that produce products transported. Each of these sections introduces models and connects theory to issues. The chapter closes with sections that provide intuitively developed models that explain the relationship between transportation and land values and wages. In each case, Button develops the relationships consistent with the classic papers in the literature. This is a superb strength of the book, wherein he both develops the history, the great thinkers, and the concepts in conjunction with one another.

Demand and costs are covered in chapters 4 and 5. Demand is not derived from principles, but rather is discussed in terms of very general neoclassical consumer demand function, with discussions of the usual comparative static shifts, elasticities, length of run, etc. He delves into the value of time and the role of quality in demand decisions and summarizes the differences in value of time across countries and studies. It was peculiar to read the section on car ownership (not often part of a transport economics book). I was captivated by the presentation and by the introduction of product life cycle theory and forecasting. Button notes shortcomings of the approach, and then points to choice model methods as a solution. This latter is extremely brief, and, in my opinion, warrants a section or chapter of its own. The cost chapter covers quite well the concepts of fixed and variable costs along with short- and long-run issues. In addition, he discusses a wide variety of cost concepts that are specific to transportation such as economies in vehicles, infrastructure, fleet, scale, scope, density and experience. As an instructor, I very much welcome this discussion, as many others try to fit transport concepts into the standard micro models, whereas Button develops the models in the context of the transport concept. Another strong feature of this chapter is the discussion of cost allocation issues. While cost allocations are present in many industries, they are of direct policy relevance in transportation, and the problems of cost allocation tend to be somewhat unique to transportation circles. I was a little surprised that the notion of a generalized cost of transportation was introduced in the cost chapter (it may be better suited for the demand chapter). Toward the end of the chapter, there is an array of topics that seem out of place, e.g., service bunching. Some of the discussion requires an equilibrium mode, and I note that following demand and costs, I did not see a chapter on firm strategy, equilibrium, and performance. That is, there is excellent material in these sections, but I might have placed them elsewhere. The final section points to statistical measurement of costs and economic efficiency. In this section, a relatively more rigorous presentation of the theoretical tenets of a cost function is presented, followed by a discussion of translog and also DEA analysis. While they are complete, they might form a larger role in the chapter.

"External Costs of Transport" is a lengthy chapter, at nearly 50 pages. It teaches students of externalities (pecuniary and technological), and then describes pollution and congestion externalities. This is followed by a very cursory description of transportation and the environment and then moves to the valuation of externalities with hedonic, travel costs, and stated preference. Unfortunately, with a more complete discussion of discrete demand decisions, the valuation of attributes would have been an excellent addition. The remainder of the chapter describes the magnitudes of environmental externalities, energy use, and congestion. These are, as with the rest of the book, complete pieces with a sense of policy, literature, and facts interpreted with the use of economic principles.

The chapter on pricing points to the complexity of pricing with regard to objective, purpose, and even market structure. Models are presented to represent shipping conferences, marginal cost pricing, short- and long-run pricing, the problem of second best, product differentiation, price discrimination, and "yield management." The comprehensive nature of this chapter sets it apart from other texts, which often focus on presentation of equilibrium models and outcomes without the institutional detail that is so important to pricing decisions. Further, at the end of the chapter, there is discussion of real world issues and concerns often ignored in other texts, e.g., the problem of a manager that must price under uncertainty from stochastic demand, peak load pricing, the lack of a core, etc.

The remainder of the book applies principles to policy, logistics, investment, planning, and forecasting. The first of these, on environmental policy, includes excellent discussions of tradable permits, pollution taxes and subsidies, adoption of environmentally better options, etc. It also describes modal energy use, policy options, and the successes of policy. I am surprised that there is not a lengthier discussion on safety issues, speed limits, and the like. The chapter on congestion is similarly handled. There is a discussion of externalities and then policy with respect to transportation, e.g., road pricing. Again, as is present throughout the book, the chapter points to the primary developers of an area—in this case, Ronald Coase, William Vickery, and Sir Allan Walters—and also presents a variety of statistics and examples which bring out some of the issues in implementation. This is extremely well done and executed.

The presentation of investment, planning and forecasting, and development (Chapter 11, 12, 13) broaden the appeal of the book and the multidisciplinary nature of transportation. These chapters, together with the logistics chapter (Chapter 10), connect business, planners, economics, and the role of investment. This sequence begins (Chapter 11) with the role of infrastructure and then covers basic principles of investments, cost benefit analysis, and the complications of transportation. The discussions include short-run and long-run presented in simple demand and cost models and the effects of capacity choices. Button compares commercial and social approaches to investment and alternative forms of financing. Students are introduced to net present value in the context of evaluating investments. The discussion leads naturally to cost/benefit analysis in the public setting. Through this discussion there is considerable discussion of Pareto optimality and the Hicks-Kaldor compensation principles, which are central to decision-making. It closes with social benefits, the practice of cost/benefit analysis, a comparison of techniques, effects on national income, and institutional considerations. The investment chapter is followed by a chapter on planning. It starts with the development of planning, the theory of planning, the use of models and forecasts, and commonly used techniques that apply to trip generation, gravity models, and disaggregate choice models. Another strong feature is that it points to major models that have been used. This provides a linkage of students into planner lingo, which is often lacking. Planners often rest investments in terms of economic development. Chapter 13 provides a historical account, introduces the Solow models, and notes its shortcomings. It then moves to new economic growth theory models and then to the relationship between transport infrastructure and economic productivity and multipliers. The chapter concludes with less developed countries, transport policies in the UK, and regional and urban. Throughout the chapter, there is considerable history, contributions of notable authors and ideas, and descriptions of factual evidence.

The final chapter of the book is on economic regulation of transport. It provides an overview of the breadth of regulations that impact transport and the theories of regulation. Button enumerates and describes a number of "rationales" for economic regulation that fall broadly into the market failure (regulation for the public interest category). He then describes instruments of regulation (a long bullet list), and at the end of the section there is a very brief discussion of the demand for regulation and captive theories of regulation. The chapter then delves modestly into the regulation of market power, with reference to the ever famous Averch-Johnson model. In addition, there are discussions on price cap regulation, contestable markets, auction models, etc. The chapter concludes with a discussion of phases of regulation and deregulation, and point to the speed of reform along with an assessment of regulatory reform. The only real complaint that I have on this chapter is that I wanted more, and I would have liked more discussion of not only regulation but deregulation. However, regulation and deregulation is quite idiosyncratic, wherein each mode has its own history, institutions, regulation, and deregulation. Hence, this recommended addition may be a book unto itself.

Overall, I strongly recommend researchers and students new to transportation, or even those that have been in the field a long time, read this book. The book can be used in the classroom, but is also a valuable research reference and an interesting read. It is easily accessible to most readers, and effectively transmits major issues, researchers, and research themes in transportation economics.

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Wilner, Frank N. Amtrak: Past, Present, and Future. *Omaha: NE: Simmons Boardman Books, Inc., 2012. ISBN 9780911 382600.*

Amtrak: Past, Present, and Future

by Melvyn A. Sacks

Frank Wilner's new book tells the story of Amtrak well. It is a sweeping and instructive story indeed.

Prior to World War II, railroads served 40 million passengers, Marquee trains like the 20th Century Limited linking New York to Chicago featured fresh cut flowers, a barber and beauty shop, elegant club cars, splendid bedrooms, and steak dinners. Railroad stations featured granite and sandstone, soaring clock towers, and arches. Meals were prepared from scratch served by impeccably dressed stewards, and after viewing the scenery in the dome car, passengers could sleep in comfortable Pullman bedrooms.

By the late 1960s with the interstate highway system largely completed and airlines becoming more attractive, private railroads were losing money on passenger service. In the 1950s, one out of every six workers in America was engaged in the automobile industry. Railroads tried to persuade the Interstate Commerce Commission to discontinue underused passenger trains. According to Peter Lyon in his book, *To Hell in a Day Coach: An Exasperated Look at American Railroads*, to make sure that passenger trains were underused, various devices were employed to discourage passengers, including engineering long delays, filthy restrooms, cabooses for passengers, and running secret trains missing from timetables. Adding to the revenue decline was the shifting of first class mail from trains to airplanes.

Railroad bankruptcies were increasing, with passenger losses a major contributor. Poor freight rail tracks hindered Amtrak with speeds as low as 15 mph on 47,000 miles of track. But public opinion was against ending national passenger service. Congress, pressed by Senator Pell (D-R.I.) and others, proposed the Rail Passenger Service Act of 1970, or Railpax, to form a government corporation and run trains under the Amtrak label, which would take over rail passenger service from the railroads. After considerable prompting President Nixon signed the legislation.

The first Amtrak president, Roger Lewis, was a poor leader and had no real interest in passenger rail, viewing this as just an ordinary paying job. But he made sure that magazines in his office were neatly in place. After Amtrak was formed, credit cards were no longer accepted, and a modern computerized reservation system would take two years to complete.

Amtrak owns no tracks, terminal yards, or repair facilities outside the Northeast corridor. In the early years of Amtrak, there were steam generators for passenger trains, incompatible electrical systems with AC and DC, and steam air conditioning on some trains. Mechanics did not know how to repair the private railroad's legacy cars. In 1972, half of the fleet was out of service, and toilets were notorious for problems. Amtrak was hindered by the private railroad's relatively poor tracks and giving priority to freight trains in violation of the Rail Passenger Service Act. Long distance trains averaged 42% on-time performance. In one week, Amtrak paid out more than $28,000 in taxis, meals, etc. for missed connections.

The average age of Amtrak cars is 25 years old, and Amfleet cars on the Northeast corridor date from 1975. There is a shortage of dining and sleeping cars. Many Amtrak locomotives are 34 years old. The Amtrak reservation system is 30 years old and hampered with outdated technology. Bus systems have discontinued servicing many smaller cities and Amtrak is often the only transportation system available.

A more hands-on approach began when Paul Reistrup became Amtrak president in 1974. Reistrup began writing Amtrak's own specifications for lightweight high horsepower locomotives. In

2011, Amtrak reported 260,000 passengers riding auto-trains annually, with more than 40 passenger coaches. Amtrak also operated contracted commuter services. In 1991, New York City passenger operations were consolidated so passengers would need to use only one station for Amtrak trains.

Still, budget cutting by Congress forced Amtrak to cut off fresh food and install pre-plated airline type food. Interest on its debt cost Amtrak $250 million in February 2002. Amtrak also had an express shipping business, moving perishable goods and priority mail on "roadrailers," which has now been discontinued.

The first higher speed train in the U.S. was the Metroliner, first run by Penn-Central in January 1969 at speeds up to 125 mph. Through the Swift Rail Development Act of 1994 it was superseded by the Acela, which entered revenue service on December 11, 2000. Acela's top speed of 150 mph is only on a small stretch of track, and the speed averages 83 mph but can be as slow as 30 mph. Acela combines electric propulsion systems with an advanced gyroscope controlled hydraulic tilt mechanism to permit higher speeds on sharp curves in the Northeast corridor. There have been problems with stability, wheel wear, and aging catenary lines. Passenger cars were found to be four inches too wide for the tilting mechanism to operate fully. There also have been disc brake hairline fractures. Acela has averaged an on-time performance of 88%.

A break from poor management that had dogged Amtrak came when David Gunn took over as Amtrak president in 2002. He complained of poor managerial controls, with financial forecasts in disarray and poor organizational structures. Gunn made considerable improvements with Amtrak, which now provides a much more reliable service. Amtrak captures 69% of the air-rail market between Washington and New York, up from 37% in 2000. Between New York and Boston, Amtrak has 52% of the air-rail market, up from 37% in 2000. Amtrak carries more passengers in the Northeast corridor than all airlines combined. The Northeast corridor carries one million intercity and commuter passengers daily with more than 2,000 trains.

In the four decades of Amtrak's existence, labor unions cooperated with Amtrak to lower costs, sustained no strikes, and otherwise ensured Amtrak's existence.

Amtrak today has 20,000 employees, runs 300 intercity and commuter trains, and has 21,000 miles of track servicing 46 states, D.C., and three Canadian provinces. It transports more than 30 million passengers annually - 10 million along the 456 mile Northeast corridor. Since 2000, Amtrak ridership has grown by 44%, and ticket revenue increased by 85%, with long distance revenue increasing by 25%. In fiscal year 2012, Amtrak served a record 31.2 million passengers. Amtrak receives 76% of operating costs from ticket sales. Amtrak operates commuter trains under contract with the states.

There is no dedicated source of Amtrak funding, however, and compared with highways and airports, the subsidy is small: For the expansion of Chicago's O'Hare airport, the federal government financed it for $6.5 billion, and for Boston's big dig, the federal government poured in $8.5 billion, but for Amtrak the yearly funding was often under $1 billion.

By comparison, high-speed rail is common in Western Europe, China, Japan, and South Korea, with speeds up to 220 mph. European and Japanese trains travel on dedicated tracks at more than twice the speed of Acela's trains.

President Obama proposed the American Recovery and Reinvestment Act of 2009, which would fund high-speed and higher speed rail in the U.S. for $37.6 billion and $15.0 billion for improving Amtrak's infrastructure and the Northeast corridor. However, Wisconsin, Ohio, and Florida cancelled the high-speed investment even though it would in many cases create thousands of high paying jobs and greatly expand commercial development. These Republican controlled states were against federal government expenditures in high-speed rail considering it not a proper role for the federal government.

High-speed rail is being considered in the U.S. 40 years after the first bullet train ran in Japan. On February 8, 2011, Vice President Biden and Transportation secretary Ray LaHood proposed a $53 billion investment plan as part of an ambitious $600 billion funding plan of high-speed and higher-speed rail. This sum depended on Congress, and many conservatives are against any spending on passenger rail, especially high-speed rail. Congress eliminated high-speed rail funding for FY 2012.

But the need is there. Aging infrastructure on the Northeast corridor hampers speed. Part of the Northeast corridor was constructed prior to the civil war, and the electrified infrastructure dates from the 1930s. There are 1,400 older bridges that will cost hundreds of millions of dollars to repair. By 2030 some 3,300 trains a day will be carrying passengers through the Northeast corridor, 40% more than in 2011. But it takes enormous public investment in track, signals, and equipment for a reliable system, which cannot be recovered from fares alone. Unless funding can be found for these essential capital projects, passenger rail will be severely hampered, with congestion and costs mounting. Large amounts of public dollars built airports and highways, and funds should also be found for Amtrak.

The lack of consistent and predictable subsidies is one of Amtrak's greatest challenges, made more difficult by federal and state budget deficits. Continued reliance on short-term Congressional appropriations hinders rational planning and investment in capital infrastructure projects. Amtrak needs a $52 billion investment in the northeast corridor to handle a projected 60% increase in intercity and commuter rail traffic. Dedicated high-speed rail would require an additional $117 billion in construction investment.

America's dependence on cars is reinforced by a shortage of other forms of transportation. Europe and Japan spends far more than the U.S. on rail transportation, and the U.S. underdeveloped passenger rail network leads to overcrowding on American highways and airports, and unlike passenger trains, road and air travel receive large subsidies. In Europe high-speed rail is replacing air travel between many cities. In Spain, between Madrid and Seville, the share of high-speed rail in the rail-air market shifted from 33% to 84%, and similar shifts to rail occurred in other parts of Europe. The result is less congestion, and a more pleasant travel experience. Also trains, especially high-speed trains, are much more environmentally friendly compared with autos, buses, and airlines. Less energy is used and with lower emissions, including CO2, which is linked to global warming.

But in Congress, privatization became the rage. In June 2011, the House Infrastructure and Transportation Committee, dominated by Republicans, considered a proposal to dismantle Amtrak and sell the Northeast corridor to private interests, undoubtedly for subsidy reductions and to remove the federal government from passenger rail. Amtrak president Joseph Boardman, pushing back, said that privatization in Britain removed economies of scale, introduced complexities and coordination problems into the system, reduced efficiencies, and required much greater subsidies than before privatization. Periodic privatization proposals are a feature in Congress.

Congress cancelled the remaining high-speed rail funding, and no money was appropriated for high-speed passenger rail in either the FY 2011 or FY 2012 budgets, considering high-speed rail investments as wasteful and even socialistic. This funding was eliminated even as China spent over $100 billion on 2,000 miles of high-speed rail, and large sums were spent on high-speed rail in Europe. Automobile taxes are much steeper in Europe than the U.S., according to sources, the price of gasoline averaging $8.63 a gallon in France, of which most of the cost are taxes. The amount of taxes available for transportation infrastructure is consequently much higher in Europe than in the U.S., and this largely accounts for the fact that the U.S. spent just $42 billion on all forms of transportation.

In conclusion, Amtrak is often the step-child of transportation, with no consistent funding, while other modes of transportation are heavily subsidized. Taxpayers have spent $40 billion on highways, more than is spent on Amtrak in its 40-year history. Amtrak has delivered a credible transportation product under trying conditions, and would deliver excellent results if only properly funded. A viable passenger rail system should be an alternative to crowded skies and highways, and if the success of European, Chinese, and Japanese high-speed trains doesn't present an embarrassment to the once mighty transportation infrastructure of the U.S., one wonders what will.

One criticism I have of the book is that perhaps more space could have been devoted to the actions of the railroads in dropping their passenger service prior to Amtrak. Their determination to rid themselves of passenger service by making it distinctly uninviting led to severe image problems when Amtrak took over, compounded by passenger equipment in disrepair, which markedly hampered Amtrak in its formative years.

Similarly, the author would have done well to expand on other nations' high-speed rail service, how it improved transportation mobility, reduced congestion, and its positive impact on reducing global warming.

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

Transportation Research Forum

Statement of Purpose

The Transportation Research Forum is an independent organization of transportation professionals. Its purpose is to provide an impartial meeting ground for carriers, shippers, government officials, consultants, university researchers, suppliers, and others seeking an exchange of information and ideas related to both passenger and freight transportation. The Forum provides pertinent and timely information to those who conduct research and those who use and benefit from research.

The exchange of information and ideas is accomplished through international, national, and local TRF meetings and by publication of professional papers related to numerous transportation topics.

The TRF encompasses all modes of transport and the entire range of disciplines relevant to transportation, including:

Economics	Urban Transportation and Planning
Marketing and Pricing	Government Policy
Financial Controls and Analysis	Equipment Supply
Labor and Employee Relations	Regulation
Carrier Management	Safety
Organization and Planning	Environment and Energy
Technology and Engineering	Intermodal Transportation
Transportation and Supply Chain Management	

History and Organization

A small group of transportation researchers in New York started the Transportation Research Forum in March 1958. Monthly luncheon meetings were established at that time and still continue. The first organizing meeting of the American Transportation Research Forum was held in St. Louis, Missouri, in December 1960. The New York Transportation Research Forum sponsored the meeting and became the founding chapter of the ATRF. The Lake Erie, Washington D.C., and Chicago chapters were organized soon after and were later joined by chapters in other cities around the United States. TRF currently has about 300 members.

With the expansion of the organization in Canada, the name was shortened to Transportation Research Forum. The Canadian Transportation Forum now has approximately 300 members.

TRF organizations have also been established in Australia and Israel. In addition, an International Chapter was organized for TRF members interested particularly in international transportation and transportation in countries other than the United States and Canada.

Interest in specific transportation-related areas has recently encouraged some members of TRF to form other special interest chapters, which do not have geographical boundaries – Agricultural and Rural Transportation, High-Speed Ground Transportation, and Aviation. TRF members may belong to as many geographical and special interest chapters as they wish.

A student membership category is provided for undergraduate and graduate students who are interested in the field of transportation. Student members receive the same publications and services as other TRF members.

Annual Meetings

In addition to monthly meetings of the local chapters, national meetings have been held every year since TRF's first meeting in 1960. Annual meetings generally last three days with 25 to 35 sessions. They are held in various locations in the United States and Canada, usually in the spring. The Canadian TRF also holds an annual meeting, usually in the spring.

Each year at its annual meeting the TRF presents an award for the best graduate student paper. Recognition is also given by TRF annually to an individual for Distinguished Transportation Research and to the best paper in agriculture and rural transportation.

Annual TRF meetings generally include the following features:

- Members are addressed by prominent speakers from government, industry, and academia.
- Speakers typically summarize (not read) their papers, then discuss the principal points with the members.
- Members are encouraged to participate actively in any session; sufficient time is allotted for discussion of each paper.
- Some sessions are organized as debates or panel discussions.

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