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On the cover: School bus safety is a community concern, but few studies have investigated the determinants of school bus crashes. Yasim Shamsunnahar, Sabreena Anowar, and Richard Tay fill this research gap in "Factors Contributing to School Bus Crashes."

A Message from the JTRF Co-General Editors

The Fall 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:

- Dertminants of VMT in urban areas
- Economic impact of congestion on freight-dependent business
- Factors contributing to school bus crashes
- Air pollution emissions associated with truck operations
- Transportation equipment replacement decision making
- Measuring spatial and temporal truck market structure
- Frequency of truck crashes on limited-access highways

In "Determinants of VMT in Urban Areas: A Panel Study of 87 U.S. Urban Areas 1982-2009," Starr McMullen and Nathan Eckstein use OLS regression as well as TSLS techniques to examine the impacts of urban density, lane miles, per capita income, fuel cost, transit mileage, and industry mix on per capita VMT. Using a distributed lag model to estimate long-run elasticities, the authors found that the long-run price elasticity of demand for per capita VMT is about five times larger than the short-run elasticity. The authors discovered that urban area per capita demand is positively and significantly related to 1ane miles, personal income, and percent of employment in the construction and public sectors. They found that fuel price, transit use, and the percent of employment in the manufacturing, retail and wholesale sectors were significantly and negatively related to per capita VMT. Also, the authors found that per capita VMT differs by geographic region, being higher the more western and the larger the population of an urban area.

Justin Taylor et al. conducted a survey of freight-dependent businesses in Washington State to calculate the costs of congestion and the economic impact of increased congestion in "The Economic Impact of Increased Congestion for Freight-Dependent Businesses." The authors found that a 20% increase in congestion experienced by commercial trucks would result in over $14 billion of increased operating costs to Washington freight-dependent industries. This translates into losses of over 27,250 jobs and $3.3 billion in economic output. The authors' survey indicated that as freight-dependent businesses spend more to provide goods, consumers would pay 60% to 80% of the increased costs. The results found that if a 20% increase in congestion occurs, the additional consumer costs would be $8.76 billion.

In "Network-Based Simulation of Air Pollution Emissions Associated with Truck Operations," Joongkoo Cho and Weihong Hu estimate greenhouse gases (CHG) and particulate matter from freight movements on California roads as well as the concurrent effects of various mitigation scenarios. The authors estimate truck freight flows between zip code areas. Then they develop a highway network model to estimate VMT on the network, based on the estimated truck flows. The results from the transportation model are used as inputs to an air pollution emission model. The authors examined the emissions impact of three policy scenarios, which are (1) replacing old trucks with newer trucks, (2) creating zero emission lanes, and (3) developing an inland port at the Mira Loma area of Los Angeles County. The authors found that the truck replacement strategy can be effective in reducing pollution in both Los Angeles County and the surrounding MSA. Zero emission lanes result in small impacts on Los Angeles County or the surrounding MSA. Developing an inland port can increase air pollution emissions in the MSA, although it can reduce emissions around the port area.

Shamsunnahar Yasim, Sabreena Anowar, and Richard Tay use a logistic regression model to identify the factors contributing to school bus collisions as opposed to collisions involving other types of buses in “Factors Contributing to School Bus Crashes.” The authors hypothesize that the factors contributing to school bus crashes are different from the factors contributing to crashes involving other types of buses. To test the hypothesis, Chi-square tests of the characteristics of SB and non-SB collisions were performed using data from Alberta, Canada. The authors found that relative to other types of buses, SB collisions are more likely to occur during the morning and afternoon peaks, in rural areas, and involve rear-end collisions by other vehicles. They are more likely to involve female drivers, drivers under 25 and older than 65, multiple vehicles, or result from passing or sideswiping collisions. The authors found that SB collisions are less likely to occur during the summer, on weekends, and under hail/sleet/snow weather conditions. The authors also found that school bus drivers are more likely to commit driving violations than non-school bus drivers.

In “Equipment Replacement Decision Making: Opportunities and Challenges,” Wei Fan, Mason D. Gemor, and Randy Machemehl discuss equipment replacement optimization (ERO). The paper is the first to use ERO SDP software that is targeted at real world application and can explicitly consider uncertainty in vehicle utilization and annual operating and maintenance cost. The authors present a dynamic programming (DP)-based optimization solution to solve the ERO problem. They also discuss Bellman’s formulation for the ERO deterministic (DDP) and stochastic dynamic programming (SDP) problems. They conclude that the SDP-based optimization solution can be of immediate use and will yield substantial cost savings for years to come in the fleet management industry worldwide.

Andrew Liang and James Nolan examine spatial aspects as well as the dynamic rates of change in the medium to long-haul grain trucking sector in West-Central Alberta and East-Central Saskatchewan in “Measuring Spatial and Temporal Market Structure in a Transportation Seetor: For-Hire Grain Trucking on the Alberta Saskatchewan Border in Canada.” The authors’ objective was to evaluate the level and scope of competition within this particular trucking sector. The authors frame the unique spatial aspects by using GIS software to build freight rate contours for this trucking market over space. The data are a unique and detailed dataset of truck rates charged to farmers for grain transportation to a common destination. A subset of this data is used to conduct an econometric estimation of short-run freight rate dynamics. The authors found evidence of less than competitive transportation markets through time and space. They find that market power is not persistent within this market, but uncompetitive pricing behavior occurs at certain times of the year.

In “Modeling Frequency of Truck Crashes on Limited Acess Highways,” Niranga Amarasingha and Sunanda Dissanayake identify the relationships between large truck crashes and traffic and geometric characteristics on limited access highways. Crash, traffic, and geometric-related data for Kansas were utilized to develop a Poisson regression model and a negative binominal regression model for understanding the relationships. Based on model fitting statistics, the negative binomial model was found to be the better model and it was used to identify the important characteristics. The authors found that large truck crash frequency increased with the length of the road section, the number of lanes, AADT per lane, and inside shoulder width. Vertical grades were significantly and negatively correlated with large truck crash frequency.

Michael W. Babcock
Co-General Editor

Kofi Obeng
Co-General Editor

Determinants of VMT in Urban Areas: A Panel Study of 87 U.S. Urban Areas 1982-2009

by B. Starr McMullen and Nathan Eckstein

This paper uses econometric techniques to examine the determinants of vehicle miles traveled (VMT) in a panel study using data from a cross section of 87 U.S. urban areas over the period 1982-2009. We use standard OLS regression as well as two-stage least squares techniques to examine the impact of factors such as urban density, lane-miles, per capita income, real fuel cost, transit mileage, and various industry mix variables on per capita VMT. We use a distributed lag model to estimate long-run elasticities and find that the long-run price elasticity of demand for per capita VMT is approximately five times larger than in the short run. Preliminary empirical results show the per capita demand for VMT in urban areas is positively and significantly impacted by lane miles, personal income, and the percent of employment in the construction and public sectors. Fuel price and transit use and the percent of employment in manufacturing, retail, and wholesale sectors are all found to be statistically significant and negatively related to VMT per capita. After correcting for endogeneity, urban population density exerts a negative, but not always statistically significant, impact on per capita VMT. Finally, per capita VMT is found to differ significantly by geographic region, being higher the more western and the larger the population size of an urban area.

INTRODUCTION

Understanding the relationship between vehicle miles traveled (VMT), economic activity, and other determinants of the demand for driving is essential for the development of an efficient U.S. transportation system. This is particularly important given recent concerns regarding the major role the transportation sector plays in producing greenhouse gas emissions (GHG). As of 2007, over 27% of the GHG in the U.S. could be traced to the transportation sector and over 75% of those were attributable to highway transportation (USDOT 2010).

Legislation at both state and federal levels aimed to reduce GHG from transportation and reduction in VMT is one policy option frequently mentioned to attain this goal. For instance, the Federal Surface Transportation Policy and Planning Act of 2009 set a directive to reduce national per capita VMT and to increase public transportation usage, intercity passenger rail services, and non-motorized transportation (Commerce Committee 2009). At the state level, the Washington state legislature adopted a direct mandate to reduce per capita VMT to 25% below 1990 levels by the year 2035 in order to reduce GHG (Winkelman, Bishins, and Kooshian 2009), and the Oregon state legislature mandated reductions in greenhouse gases (GHG) of 10% below 1990 levels by 2020 and 75% below 1990 levels by 2050 and expects the transportation sector to play a crucial role in the achievement of this goal (Oregon House Bill 3543, 2007).

USDOT (2010) mentions VMT reduction as one of several ways to reduce GHG from transportation, with increased fuel efficiency, development of alternative fuels, and changes in vehicle and system operations being other important ways to help reduce energy consumption and GHG from transportation. As Boarnet (2010) notes, this is a complex issue since VMT reduction is really just a proxy for GHG reduction and thus should probably serve as one of many intermediate targets to help reduce GHG, not as the end goal itself.

Concerns have been expressed regarding the impact of VMT reduction policies. Pozdena (2009) has claimed that at the national level, VMT changes lead to reductions in GDP, thus suggesting that

VMT reduction policies could be detrimental to overall economic activity. However, recent research by McMullen and Eckstein (2012) has shown that at the national level, VMT changes derive from GDP changes and, when individual urban areas in the U.S. are examined, there is little significant causality found between VMT and income. Puentes and Tomer (2008) argue that other factors, such as the increased availability of transit, telecommuting, and on-line retail activity that provide substitutes to mobility, weaken any possible causal link from VMT to GDP.

The question then becomes what factors to consider when designing VMT reduction policies so as to minimize adverse impacts. Carlson and Howard (2009) point out that the impact of VMT reduction policies will differ depending on the geographical area considered. They argue that VMT reduction policies are best implemented in urban areas (rather than rural areas) where there are more viable options available for VMT reduction policies such as the availability of alternative modes of travel, including transit ridership, bicycling and walking, land use policies to increase urban density and reduce commute distances, increased use of carpooling, etc. Further, since the majority of the U.S. population lives in urban areas, it makes sense to first concentrate VMT efforts in urban locations.

Accordingly, we explore the relationship between VMT and economic activity using a panel data set of 87 U.S. urban areas from 1982-2009 provided by the Texas Transportation Institute (TTI). Multiple factors are hypothesized to contribute to VMT demand, including lane miles, personal income, population density, fuel cost, transit use, and the percent of employment in the public sector, finance, construction, manufacturing, and wholesale sectors. Results should assist policymakers in tailoring VMT reduction policies for urban areas in a way that will have the least adverse impact on mobility and economic activity.

LITERATURE REVIEW: DETERMINANTS OF VMT IN URBAN AREAS

Economic theory suggests some basic determinants of demand for a product: price, income, and population (when more than one consumer is considered). VMT per capita (VMTPC) will be considered as the good or product of interest in this paper.

Since VMT is usually considered to be a normal good, higher incomes are expected to result in more driving and thus VMTPC, ceteris paribus. Accordingly, personal income per capita (PIPC) is included as an indicator of the average income in urban areas. Positive income elasticities of demand are found consistently in the literature and range from 0.05 to 0.62 in the short run, and 0.12 to 1.47 in the long run (Goodwin, Dargay, and Hanly 2004).

Average annual state gasoline prices in real 2005 dollars (RFC) are used to represent the price or marginal cost of driving. Although there are certainly other components that are attributed to the price of driving (such as insurance, wear and tear on the vehicle, driving time, etc.), the price of gasoline is a large component and the data are easily available. Additionally, the real price of fuel (RFC) has been used in other studies as a proxy for the price of driving (Zhang et al. 2009; McMullen et al, 2010; Fulton et al. 2000; and Noland 2001). Price elasticities of demand for driving are expected to be negative and have been found to be in the range from –0.17 to –0.05 in the short run, and –0.63 to –0.10 in the long run (Goodwin, Dargay, and Hanly 2004).

Another possible determinant of VMTPC in urban areas is population density: as population becomes more dispersed and distances rise, VMT should rise. Accordingly, population density (DENSITY) is expected to be negatively correlated to VMTPC.

Increasing urban density through land use policy has been frequently mentioned as a possible VMT reduction policy based on evidence of the massive decentralization of employment in metropolitan areas between 1950 and 1990 that has led to longer commutes and more driving (Baum-Snow 2010). Research that examines smart growth, urban growth boundaries, and mixed development finds that denser development allows for shorter routes, more one stop shopping, and more walking and biking options, thus reducing the need for vehicle travel (Winkelman, Bishins, and

Kooshian 2009; Frank and Pivo 1995; and Litman 2010). However, increasing urban area densities through land use policies could cause increases in housing prices that would partially negate the desired VMT reduction (Moore et al. 2010). Boarnet (2010) concludes that VMT reduction will require a combination of pricing and land use policies and suggests that policies that are successful in some regions may not make sense for others.

To incorporate VMT substitutes (substitutes for driving) into the model, transit passenger miles traveled per capita (PMTPC) is included as an explanatory variable and is anticipated to have a negative elasticity, as found in similar studies (Pushkarev and Zupan 1980 and Holtzclaw 1991). Transit ridership in an urban area is expected to be negatively related to VMT as transit availability presents the consumer an alternative to driving.

Finally, the industry mix in different areas may result in more or less VMT, depending on the requirements of the industry. Given trends in the use of the Internet, we might expect certain industry sectors, such as retail where Internet shopping can occur at a remote location by computer as opposed to driving to a physical location, to generate less VMT than other economic activities that may require driving to a physical location. For instance, it is plausible that an industry sector like construction, which requires large amounts of movements of labor and supplies, may be more VMT-intense than an industry sector such as finance, which allows for money, advice, and services to take place either over the phone, fax, or Internet, replacing driving.

Baum-Snow's (2010) observation that firms that do not require a central city location (such as manufacturing or wholesale) often operate at the periphery of an urban area to be closer to where workers live, suggests lower VMT for workers employed in those sectors. While many firms have relocated outside the central city, thus possibly reducing commute distance for suburban workers, there are some sectors that may be more dependent on central city locations. For instance, public sector employees may have no choice but to commute to specific government work sites in central cities, making commute distances and VMT higher for those public sector employees living in the suburbs, relative to employees of private firms that have more flexibility to locate outside of the central city and closer to suburban workers.

Thus, this study incorporates industry employment mix variables, adding a new and important feature to the VMT derived demand model. Industry mix variables are defined here to be the percent of an urban area's economy that is employed in certain industries, allowing for direct evaluation of the per capita VMT intensity of industries during the production, distribution, and sales processes.

Finally, the most challenging variable to consider is that relating to the highway investment in an urban area, as usually measured by lane miles (LM) or lane miles per capita (LMPC). The literature suggests that LM is not truly exogenous in respect to VMT or VMTPC. It has been demonstrated that increases in VMT increase the demand for road capacity and can lead to more lane miles being built. Moreover, increases in lane miles of highway will reduce the cost of driving and induce more VMT, leading to a significant simultaneity bias (Noland 2001; Fulton et al. 2000; Goodwin 1996; and Pells 1989).

METHODOLOGY

Standard OLS Model

We follow previous studies and use VMTPC as the dependent variable for our econometric specification (Noland and Cowart 2000, Fulton, et al. 2000). Accordingly, the VMTPC equation is:

$$(1)\quad \log(VMTPC_{it}) = \mathrm{c} + \alpha_i + \beta_t + \sum_k \lambda^k * \log(X^k_{it}) + \varepsilon_{it}$$

Where:

- $VMTPC_{it}$ is the average daily freeway and arterial vehicle miles traveled per capita for urban area *i* in year *t*;
- c is a constant term for the entire sample;
- α_i is the group-specific fixed effect for urban area *i*;
- β_t is the time-specific fixed effect for year *t*;
- λ_k is the coefficient of the k^{th} explanatory variable;
- X^k_{it} is the value of explanatory variable *k* for urban area *i* and year *t*.
- ε_{it} is the error term of a random variable for urban area *i* in year *t*, assumed to be normally distributed with mean zero.

The model transforms all variables (except for the fixed effect dummies) into natural logarithms, making the coefficients easily interpreted as elasticities and to help avoid heteroskedasticity. Note that the group-specific fixed effect can be defined as regional grouping, or TTI population size grouping instead of urban area (see Appendix A for categorical definitions and a list of urban areas in each group). These different group-specific fixed effects allow for interpretation of important relationships between VMTPC and region or population size, but provide less total information because they incorporate a smaller number of less specific dummy variables.

Distributed Lag Model

The distributed lag model, as used in Noland and Cowart (2000), is written as:

(2) $$\log(VMTPC_{it}) = c + \alpha_i + \beta_t + \gamma * \log(VMTPC_{it-1}) + \sum_k \lambda^k * \log(X^k_{it}) + \varepsilon_{it}$$

Where all specifications are identical to the previous fixed effects OLS model, except for the inclusion of $VMTPC_{it-1}$, the one-year lagged value of average daily freeway and arterial vehicle miles traveled per capita for urban area *i* in year *t-1*, so this reduces the number of time periods used by one.

The distributed lag model differs from the basic model by incorporating a lagged value of the dependent variable (VMTPC) on the right-hand side of the equation. This allows for the calculation of long-term and short-term elasticities, where the long-term elasticities are defined as $\varepsilon = \frac{\lambda}{1-\gamma}$, where λ are the short-run elasticities (found in the regression's coefficients), and γ is the coefficient of the one-year lag of VMTPC. The model assumes an exponential lag structure that shows short-run impacts to be greatest and to diminish exponentially over time (Noland and Cowart 2000).

Two-Stage Least Squares Model

To deal with the endogeneity problem noted above for lane miles (LMPC), a two-stage least squares (2SLS) model is used, requiring the selection of an appropriate instrumental variable. Following Noland and Cowart (2000) and given data availability, urban land area (ULA) is selected as the instrument of choice. The first and second stages of the 2SLS model are written as:

(3) $$\log(LMPC_{it}) = c + \alpha_i + \beta_t + \sum_k \lambda^k * \log(X^k_{it}) + \gamma * \log(ULA_{it}) + \varepsilon_{it}$$

(4) $$\log(VMTPC_{it}) = c + \alpha_i + \beta_t + \sum_k \lambda^k * \log(X^k_{it}) + \gamma * \log(\overline{LMPC})_{it} + \varepsilon_{it}$$

Where all specifications are identical to the model already specified except that X^k_{it} no longer includes the endogenous variable, LMPC. ULA_{it} is the square miles of land area within urban area *i* in year *t*, and $\overline{LMPC}_{it}$ is the predicted estimate of LMPC within urban area *i* in year *t* taken from the first stage regression. Again all variables are natural logarithms.

As is expressed in the above set of equations, to incorporate 2SLS into the model, urban land area (*ULA*) is added to the first stage, which predicts LMPC using all available instruments. Then, the predicted estimate $\overline{LMPC}_{it}$ is applied to the VMTPC equation in the second stage, removing the simultaneity bias.

An appropriate instrumental variable must be both relevant, in that it is significantly related to the endogenous variable being instrumented, but also exogenous in that it is not correlated with the error term in the explanatory equation. Exogeneity ensures that the instrument's only influence on the dependent variable is through its effect on the endogenous variable and that it should not be an independent variable of the model in its own right (for further details on 2SLS and instrumental variables see Greene [2008]).

Econometric tests are performed to see if the model supports the use of ULA as an instrument. First, a Durbin-Wu-Hausman test for endogeneity of LMPC is performed. Next, tests are applied to determine the relevance of the instrument. Finally, the exogeneity of the instrument itself, ULA, is examined.

A Durbin-Wu-Hausman test for endogeneity uses the null hypothesis that the possible endogenous regressor, LMPC, is exogenous. It compares estimates from the corresponding 2SLS and OLS regressions to see if differences between the two estimates are statistically significant. With ULA as the instrument in the 2SLS model, the Durban-Wu-Hausman test gave a statistically significant Chi^2 (8) test statistic equal to 38.64. Thus, the null hypothesis is rejected, suggesting that LMPC is endogenous, indicating the use of a method such as 2SLS.

Next, a highly significant negative t-statistics is found for ULA in the first stage of the 2SLS, implying that ULA is sufficiently related to LMPC to make it "relevant" and appropriate for use in the 2SLS. Additionally, ULA has a fairly low correlation with VMTPC of 0.32, which indicates its exogeneity and that it does not need to be included in the model in its own right. Hence, ULA is used as an instrument, because through a survey of the literature on this simultaneous relationship between lane miles and vehicle miles traveled, no clearly exogenous instrument is found to be more relevant than urban land area.[1]

DATA

In addition to VMT and VMTPC, explanatory variables used in this analysis are defined as:

- LMPC: freeway and arterial lane miles per capita
- PIPC: personal income per capita in 2005 dollars
- RFC: state average price of fuel in real 2005 dollars
- PMTPC: transit passenger miles traveled per capita for the urban area
- DENSITY: number of residents per square mile
- CON, MANU, FIN, WHOLE, RETAIL (industry employment variables): the percent of total employment in the relevant industry in the relevant MSA
- PUB: the ratio of public to private employees in relevant MSA

The data for urban areas have been collected and published by the Texas Transportation Institute (TTI) since 1982 for use in its annual Urban Mobility Report (UMR) (Texas Transportation Institute 2011). The definition of urban area does not change over time in this data set. From this dataset, average daily VMT on freeways and principal arterial roads is used as the urban area VMT variable for this study. These VMT estimates are compiled by TTI from the Highway Performance Monitoring System (HPMS) database and other local transportation data sources and are put into per capita form using population estimates from the U.S. Census Bureau.

Because urban area GDP data is unavailable, this study substitutes metropolitan statistical area (MSA) personal income data for the MSAs that coincide with the TTI urban areas. Note that at the national level, correlation between personal income and GDP is .999, making PI a good proxy for GDP. See U.S. Census Bureau (2010) and Office of Budget and Management (2010) for urban area and MSA definitions. Personal income, in real 2005 dollars, is also from the BEA (U.S. Department of Commerce 2011).

TTI collects detailed data on 100 individual urban areas in the U.S. and categorizes these urban areas into four population size groupings: very large (vlg), large (lrg), medium (med), and small (sml) (see Appendix A for categorical definitions and a list of urban areas in each group). These groupings are important, as it is likely that VMT reduction policies will be implemented in larger urban areas first, because they have the largest GHG reduction potential and also suffer the worst congestion delays. Thus, it is important to observe if variations in the size of an urban area affects the causal relationship between VMT and economic activity. Of these 100 urban areas, two are not core urban areas inside an MSA, and without this distinction personal income data were not available. Table 1 provides summary average annual statistics for *VMT*, personal income (PI), and population variables for the 98 TTI urban areas for the period 1982-2009.

Of these 98 TTI urban areas, some were not included in the 2007 UMR, and hence did not have annual data on two key variables needed in this analysis: urban land area (ULA) and population density (DENSITY). Thus, this study of derived demand includes only the 87 urban areas for which complete data sets were available for the entire time period. The panel data set used here includes specific DENSITY, LMPC, RFC, and PMTPC variables, all from the 2010 UMR (TTI 2011) for the sample of 87 urban areas. The source for PIPC and the industry employment statistics is BEA for the 87 associated MSAs (U.S. Department of Commerce 2011).

Table 2 presents summary statistics for the variables used in this paper. These statistics do not exactly match those found in Table 1 because this table includes data for only 87 of the 98 urban areas in Table 1. On average between 1982 and 2009, individuals in these 87 urban areas drove over 16 miles a day on freeways and arterial roads, were passengers on 124 miles of public transit annually, earned an average annual income of nearly $32,000 in real 2005 dollars, and paid nearly $2 a gallon for gas in real 2005 dollars.

The statistical package used for these estimations was STATA.

RESULTS

The inclusion of “two-way’ fixed effects in which dummy variables are specified for both an observation’s group (urban area) and time period (year) provides a static coefficient estimate for the entire sample, while dynamically shifting the constant term for each observation. This allows unmeasured or unknown cross-sectional (urban area) and time-series (year) factors to be explained through the fixed effects’ coefficients and reduces any remaining bias due to omitted variables that are inevitably left out of the model (Dougherty 2007).[2]

The fixed effect coefficients in this study control for potential omitted variables, such as the number of women in the workforce, car ownership, population growth, climate, the existence of driving alternatives not measured by the PMTPC transit variable such as walking/biking paths, telecommuting, along with other unknown or unmeasured factors.

F-statistics are used to test the significance of the fixed effects, with the null hypothesis that the fixed effects are not jointly significantly related to VMTPC. First a comparison is made between a standard OLS model and a model with group-specific effects, resulting in a significant F-statistic of $F (86, 2267) = 104.72$. Then, the model with only the group-specific effects is compared to a model with group and time-specific or “two-way” effects fixed model, resulting in a significant $F(27, 2240) = 23.94$. Both results allow for a rejection of the null hypothesis and support the use of “two-way” fixed effects in the model estimation (Greene 2008).

Table 1: Urban Area Daily VMT Summary Statistics (1982-2009)

Variable Name	Mean	Std. Dev.	Min	Max	% Annual Growth
VMT	23,200,000	33,100,000	550,000	268,000,000	2.75%
VMT (vlg)	83,600,000	52,900,000	24,000,000	268,000,000	2.55%
VMT (lrg)	23,200,000	10,700,000	4,700,000	61,600,000	3.08%
VMT (med)	10,000,000	4,288,686	1,720,000	26,100,000	2.89%
VMT (sml)	4,914,278	2,563,854	550,000	11,800,000	2.96%
VMTPC	16.50	3.84	5.50	29.51	1.32%
VMTPC (vlg)	16.55	3.78	7.01	24.32	1.33%
VMTPC (lrg)	16.72	3.34	8.01	23.86	1.52%
VMTPC (med)	16.53	3.67	5.76	26.18	1.30%
VMTPC (sml)	16.14	4.58	5.50	29.51	1.14%
UA Pop.	1,436,062	2,267,139	95,000	18,800,000	1.34%
UA Pop. (vlg)	5,416,923	3,962,287	1,430,000	18,800,000	1.20%
UA Pop. (lrg)	1,366,139	510,278	365,000	3,048,000	1.54%
UA Pop. (med)	592,735	164,021	170,000	1,100,000	1.57%
UA Pop. (sml)	286,997	947,378	95,000	510,000	1.79%
PI (000,000)	$59,700	$95,300	$136,000	$959,000	2.70%
PI (vlg) (000,000)	$209,000	$45,700	$134,000	$282,000	2.67%
PI (lrg) (000,000)	$54,800	$12,900	$34,500	$74,700	2.83%
PI (med) (000,000)	$25,100	$5,030	$16,900	$33,100	2.48%
PI (sml) (000,000)	$13,600	$3,230	$8,750	$18,800	2.83%
PIPC	$31,204	$7,112	$11,822	$74,954	1.43%
PIPC (vlg)	$36,845	$4,577	$28,289	$44,396	1.48%
PIPC (lrg)	$32,174	$3,982	$25,039	$38,134	1.41%
PIPC (med)	$31,191	$3,618	$24,589	$37,022	1.41%
PIPC (sml)	$28,242	$3,306	$22,433	$33,333	1.34%
MSA Pop.	1,730,465	2,396,915	111,106	19,100,000	1.24%
MSA Pop. (vlg)	5,599,903	551,734	4,742,498	6,492,596	1.17%
MSA Pop. (lrg)	1,681,714	196,184	1,376,848	2,004,722	1.40%
MSA Pop. (med)	795,784	69,622	686,925	911,835	1.05%
MSA Pop. (sml)	475,742	58,862	389,911	578,215	1.47%

Table 2: Sample of 87 Urban Area's Summary Statistics (1982-2009)

Variable Name	Mean	Std. Dev.	Min	Max
Vehicle Miles Traveled (VMT)	25,450,000	34,580,000	550,000	265,290,000
Vehicle Miles Traveled Per Capita (VMTPC)	16.44	3.83	5.50	29.51
Urban Area Population (POPu)	1,572,530	2,369,525	95,000	18,768,000
Population Density (DENSITY)	2,244	898	989	5,767
Urban Land Area (ULA)	643	659	25	4,810
Lane Miles (LM)	3,450,211	4,125,103	175,000	27,020,000
Lane Miles Per Capita (LMPC)	2.52	0.61	1.21	5.03
Real Fuel Cost (RFC)	$1.96	$0.54	$1.11	$3.72
Transit Pass. Miles of Travel (000,000) (PMT)	457	1,905	1.40	21,699
Transit Pass. Miles of Travel Per Capita (PMTPC)	124.30	148.72	1.97	1163.95
Personal Income (000,000) (PI)*	$65,373	$99,722	$1,364	$958,964
Personal Income Per Capita (PIPC)*	$31,613	$7,014	$11,822	$74,954
MSA Population* (POPm)	1,883,582	2,502,117	111,106	19,069,796
Public Private Employment Ratio (PUB)*	18.66%	7.56%	8.24%	58.71%
Percent Finance-Ins.-Real Estate Employment(FIN)*	8.34%	1.87%	0.34%	17.76%
Percent Construction Employment (CON)*	5.68%	1.36%	2.95%	14.85%
Percent Manufacturing Employment (MANU)*	10.91%	5.40%	1.01%	32.06%
Percent Wholesale Employment (WHOLE)*	4.51%	1.21%	1.83%	9.26%
Percent Retail Employment (RETAIL)*	14.88%	3.15%	7.46%	27.54%

**Represents that statistics are from MSAs and not UAs*

Standard OLS Results

Table 3 displays the estimated model with four sets of different industry employment variable specifications, ordered in columns from (A) to (D). Column (A) only includes the public-private employment ratio (PUB) and no other industry sector variables. This specification gives a large significantly positive coefficient for PUB and produces the largest R-squared of the four regressions, but fails to provide in-depth examination of specific industries effects on VMTPC—other than suggesting that urban areas with higher ratios of public to private employment have higher VMT.

To provide more insight on the impact of industry-specific variables within the private sector, we use the specification in Column (B), which includes all five of the industry employment variables, to see if they have any impact on VMT when public sector employment is not considered. Of these five variables, only construction (CON) has a positive and significant impact on VMTPC and only manufacturing (MANU) significantly reduces VMTPC. Column (C) omits the insignificant industry employment variables found in Column (B), leaving only construction and manufacturing; doing this increases the R-squared by about 1%.

Column (D) uses percent wholesale employment (WHOLE) instead of MANU, and has a much larger R-squared than Column (C). While the WHOLE sign is negative, it does not become significant until the simultaneity bias is removed, as shown below in the 2SLS model results. Column (D), which includes specific urban area and yearly fixed effects, does not report fixed effects coefficients for each individual urban area and year for the sake of brevity (available from authors on request).

LMPC, PIPC, RFC, and PMTPC all give expected signs and are statistically significant at the 5% level in all four columns of Table 3. However, the DENSITY coefficient sign varies between

Table 3: OLS Fixed Effects Model with Varying Employment Mix Variables (1982-2009) Dependent Variable: VMTPC

Variable Name	(A) UA & Year Effects	(B) UA & Year Effects	(C) UA & Year Effects	(D) UA & Year Effects
Lane Miles Per Capita (LMPC)	.4902* (27.47)	.4865* (27.88)	.4941* (29.15)	.4994* (28.10)
Personal Income Per Capita (PIPC)	.3127* (9.68)	.1358* (3.97)	.1606* (4.82)	.2487* (7.38)
Population Density (DENSITY)	-.0087 (-0.55)	.0198 (1.26)	.0162 (1.05)	-.0152 (-0.96)
Real Fuel Cost (RFC)	-.1231* (-3.96)	-.1431* (-4.67)	-.1351* (-4.46)	-.1263* (-4.02)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0193* (-4.08)	-.0189* (-4.04)	-.0194* (-4.23)	-.0176* (-3.70)
Public Private Employment Ratio (PUB)	.0663* (3.49)			
Percent Finance-Insure-Real Estate Employment(FIN)		.0074 (0.70)		
Percent Construction Employment (CON)		.0697* (4.59)	.0607* (4.09)	.0338* (2.22)
Percent Manufacturing Employment (MANU)		-.1636* (-12.19)	-.1659* (-12.72)	
Percent Wholesale Employment (WHOLE)		-.0113 (-0.63)		-.0061 (-0.33)
Percent Retail Employment (RETAIL)		-.0521 (-1.43)		
Constant	-.6953* (-1.98)	.5619 (1.45)	.4066 (1.08)	-.0340 (-0.09)
Number of Urban Areas	87	87	87	87
Number of Years	28	28	28	28
Number of Total Obs.	2436	2344**	2422**	2361**
R-squared	0.5577	0.3958	0.4055	0.5529
Degrees of freedom	2314	2218	2299	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level.*
***Smaller number of observations due to missing observations from BEA employment statistics*

regressions and is not found to be statistically significant in any of the four models. This is not consistent with expectations or the results of previous studies (Noland and Cowart 2000) that find the coefficient of DENSITY to be negative and significant across all specifications. This may be because of DENSITY's strong correlation with LMPC, which is known to feature a strong simultaneity bias. Also, previous studies did not include variables to capture the impact of alternative modes such as transit or the employment mix of the urban area.

Table 4 includes the same independent variables as Column (D) of Table 3, but also includes variables indicating the size of the urban area (small, medium, large, and very large) and geographic location (eastern, central, and western). For instance, Column (B) uses regional groupings for urban areas in the eastern, central, and western part of the U.S.; so that western is omitted as the control

Table 4: OLS Fixed Effects Model with Varying Group Effects (1982-2009)
Dependent Variable: VMTPC

Variable Name	(A) No Group Effects	(B) Regional & Year Effects	(C) Pop. Size & Year Effects	Standard OLS (column D Table 3)
Lane Miles Per Capita (LMPC)	.4974* (28.37)	.4709* (27.27)	.5065* (29.67)	.4994* (28.10)
Personal Income Per Capita (PIPC)	.5363* (28.25)	.5413* (28.15)	.4351* (21.60)	.2487* (7.38)
Population Density (DENSITY)	.0408* (3.40)	-.0120 (-0.94)	.0084* (0.70)	-.0152 (-0.96)
Real Fuel Cost (RFC)	-.1681* (-3.32)	-.4547* (-8.00)	-.0450* (-0.88)	-.1263* (-4.02)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0274* (-5.52)	-.02667* (-5.51)	-.0461* (-8.73)	-.0176* (-3.70)
Percent Construction Employment (CON)	.2460* (15.01)	.1883* (10.80)	.2310* (14.01)	.0338* (2.22)
Percent Wholesale Employment (WHOLE)	.1324* (9.54)	.1581* (11.40)	.0699* (4.90)	-.0061 (-0.33)
Central Region (CENTRAL)		-.0918* (-8.57)		
Eastern Region (EASTERN)		-.1079* (-10.89)		
Very Large Population Size (VLG)			.0874* (6.73)	
Large Population Size (LRG)			.0588* (6.71)	
Small Population Size (SML)			-.0806* (-8.37)	
Constant	-2.216 (-9.83)	-1.561 (-6.48)	-1.254 (-5.38)	-.0340 (-0.09)
Number of Urban Areas	87	87	87	87
Number of Years	28	28	28	28
Number of Total Obs.	2361	2361	2361	2361
R-squared	0.6372	0.6552	0.6630	0.5529
Degrees of freedom	2238	2236	2235	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level.*

group (see Appendix A for a list of urban areas in each group). The negative coefficients on both the central and eastern regional dummies indicate that ceteris paribus, VMTPC is higher in the western urban area regional grouping. This could be due to smaller population density of western urban areas or larger land areas and distances between major cities, along with a number of other regional factors.

Column (C) uses population size groupings for very large, large, medium, and small urban areas as fixed effects; so that medium is omitted as the control group (see Appendix A for categorical definitions and a list of urban areas in each group). The coefficients indicate that VMTPC increases with population size. However, since policy is more likely to be implemented at the metropolitan area level than on a regional level or by urban area size specification, we have selected to use the urban area fixed effects rather than other geographic fixed effects for the rest of this analysis.

Finally, Table 4, Column (A) is included to show a regression with no group-specific fixed effects. However, as noted earlier, the F tests shows that the use of urban area-specific fixed effects and yearly fixed effects provide the best fit for the model, as in column D (reproduced from Table 3). Accordingly, we use urban area and yearly fixed effects rather than the population size or regional dummy variables, along with CON and WHOLE for industry mix, in the rest of this analysis.

Distributed Lag Results

Table 5 presents a distributed lag regression output and provides the calculated long-run elasticities for the independent variables. The long-run elasticities found in Column (B) are closely comparable to the coefficients from the standard fixed effects model Column (D) from Table 3, which is labeled in Table 5 as Column (D) for comparison. Alternatively, the short-run elasticities, which are found in the distributed lag regression's coefficients, and shown in Column (A) are considerably smaller.

Recall that the long-term elasticities are calculated as $\varepsilon = \frac{\lambda}{1-\gamma}$, where are the short-run elasticities (found in the regression's coefficients), and is the coefficient of the one-year lag of VMTPC. We find a very inelastic price elasticity in the short-run of -.0263 (the RFC coefficient in Table 5), while the long-run price elasticity is $\frac{-.0263}{1-.7961} = -.1290$, which is very close to the value of -.1263 [found in the standard fixed effects model in Column (D)].

Thus, the long-run price elasticity found here is approximately five times larger than the short-run elasticity of demand for VMTPC, as compared by Noland and Coward (2000), who found the long-term price elasticity to be about 3.5 times as large as the short-run elasticity. Note that the larger R-squared in the distributed lag model is simply an artifact of the strong relation between VMTPC and its lag and does not necessarily reflect a superior design.

Two-Stage Least Squares Results

This section depicts the instrumental variable two-stage least squares model that corrects for the endogeneity of LMPC.

Table 6 shows the first stage of the 2SLS model, with LMPC as the dependent variable being explained by the instrument, ULA, and all the other exogenous variables in the equation. In all four columns, ULA has a negatively significant coefficient. Additionally, in the first stage, one can see that DENSITY is strongly negatively correlated to LMPC. This relation helps explain why the DENSITY coefficient in the standard fixed effects model is biased away from its expected negative value.

The second stage regressions are presented in Table 7. All variables in the model specifications in Columns (A) and (D) are significant at the 5% level, and coefficients have signs consistent with expectations of economic theory. Finally, the specifications in columns (A) and (D) have the largest R-squared of any of the four 2SLS models, indicating the best econometric fit.

Table 5: Distributed Lag Model (1982-2009)
Dependent Variable: VMTPC

Variable Name	(A) Distributed Lag Model	(B) Long-Run Elasticity from (A)	Standard OLS (column D from Table 3)
Lagged VMTPC One Year (L1_VMTPC)	.7961* (66.65)		
Lane Miles Per Capita (LMPC)	.1050* (8.71)	.5150	.4994* (28.10)
Personal Income Per Capita (PIPC)	.0498* (2.44)	.2442	.2487* (7.38)
Population Density (DENSITY)	-.0210* (-2.24)	.1030	-.0152 (-0.96)
Real Fuel Cost (RFC)	-.0263 (-1.47)	-.1290	-.1263* (-4.02)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0038 (-1.33)	-.0186	-.0176* (-3.70)
Percent Construction Employment (CON)	.0104 (1.15)	.0510	.0338* (2.22)
Percent Wholesale Employment (WHOLE)	.0024 (0.22)	.0118	-.0061 (-0.33)
Constant	.1888 (0.80)		-.0340 (-0.09)
Number of UAs	87		87
Number of Years	28		28
Number of Total Obs.	2344		2361
R-squared	0.9673		0.5529
Degrees of freedom	2220		2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level.*

It is notable that, after correction for simultaneity, DENSITY is found to have a negative coefficient in all four model specifications, but it is only significant in models shown in Columns (A) and (D). The DENSITY coefficients in Columns (B) and (C) here are negative (as opposed to positive as found for these models in the OLS specification) but not statistically significant. Although this result is consistent with the hypothesis that increases in urban density reduce VMTPC, the lack of statistical significance and the large change in the size of the coefficient across models is of concern and deserves further study.

The 2SLS correction significantly decreased the LMPC elasticity from .4994 in the standard OLS model to .2524 in the 2SLS. This smaller result is more comparable to the LMPC elasticities found in the literature (Noland 2001; Fulton et al. 2000).

The estimated coefficient for transit ridership per capita (PMTPC) is consistently negative and significant across all specifications and the size of this coefficient actually increases slightly with the 2SLS estimation. This result is consistent with the expectation that urban areas with higher transit ridership per capita have lower VMT per capita.

Table 6: 2SLS Model- First Stage (1982-2009)
Dependent Variable: LMPC
Instrument: ULA

Variable Name	(A) 2SLS	(B) 2SLS	(C) 2SLS	(D) 2SLS
Urban Land Area (ULA)	-.3948* (-21.67)	-.4112* (-22.27)	-.4226* (-23.07)	-.4128* (-22.25)
Personal Income Per Capita (PIPC)	.0705* (2.05)	.0041 (0.11)	-.0282 (-0.76)	.0407 (1.12)
Population Density (DENSITY)	-.4108* (-19.27)	-.4023* (-18.48)	-.4448* (-20.97)	-.4176* (-19.20)
Real Fuel Cost (RFC)	-.1428* (-4.34)	-.1260* (-3.75)	-.1505* (-4.50)	-.1199* (-3.55)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0009 (-0.17)	.0016 (0.31)	.0020 (0.40)	.0027 (0.53)
Public Private Employment Ratio (PUB)	.1904* (9.59)			
Percent Finance-Insure-Real Estate Employment(FIN)		-.0299* (-2.57)		
Percent Construction Employment (CON)		-.0080 (-0.48)	-.0161 (-0.98)	-.0223 (-1.36)
Percent Manufacturing Employment (MANU)		-.0623* (-4.22)	-.0552* (-3.82)	
Percent Wholesale Employment (WHOLE)		-.1002* (-5.10)		-.0937* (-4.76)
Percent Retail Employment (RETAIL)		-.1016* (-2.53)		
Constant	6.048 (13.79)	5.704 (11.86)	7.000 (14.94)	5.809 (12.18)
Number of UAs	87	87	87	87
Number of Years	28	28	28	28
Number of Obs.	2436	2344	2433	2361
R-squared	0.1506	0.1315	0.1504	0.1484
Degrees of freedom	2314	2218	2299	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level*

Column (D) in Table 7 is the final model used to calculate other elasticities. From this we observe that a 10% increase in personal income per capita (PIPC) results in just over a 2.6% increase in VMTPC (due to the coefficient of .263). LMPC behaves similarly, with a 10% increase in lane miles per capita, resulting in just over a 2.5% increase in VMTPC (due to the coefficient of .2524). RFC, DENSITY, and PMTPC all show significantly negative elasticities of -.1542, -.0431, and -.0228, respectively.

As far as the industry specific coefficients are concerned, from Column (A) we note that a 10% increase in the ratio of public to private sector employment results in a 1.2% increase in VMTPC. This is consistent with the hypothesis that public sector employees living outside of the central city may have longer commutes to work than private sector employees who may be able to live closer to their job locations in the suburbs.

Table 7: 2SLS Model with Different Employment Mix Variables (1982-2009)
Second Stage Dependent Variable: VMTPC
Instrument: ULA

Variable Name	(A) 2SLS with UA & Year Effects	(B) 2SLS with UA & Year Effects	(C) 2SLS with UA & Year Effects	!(D) 2SLS with UA & Year Effects
Predicted Lane Miles Per Capita ($\overline{LMPC}_{it}$)	.2753* (6.14)	.2684* (6.36)	.3315* (8.31)	.2524* (5.80)
Personal Income Per Capita (PIPC)	.3425* (10.14)	.1424* (4.02)	.1630* (4.79)	.2630* (7.47)
Population Density (DENSITY)	-.0343* (-2.03)	-.0026 (-0.16)	-.0077 (-0.47)	-.0431* (-2.52)
Real Fuel Cost (RFC)	-.1534* (-4.71)	-.1687* (-5.26)	-.1591* (-5.07)	-.1542* (-4.67)
Transit Pass. Miles Travel Per Capita (PMTPC)	-.0247* (-4.96)	-.0237* (-4.83)	-.0231* (-4.87)	-.0228* (-4.53)
Public Private Employment Ratio (PUB)	.1207* (5.44)			
Percent Finance-Insure-Real Estate Employment(FIN)		-.0004 (-0.04)		
Percent Construction Employment (CON)		.0716* (4.55)	.0595* (3.93)	.0332* (2.09)
Percent Manufacturing Employment (MANU)		-.1742* (-12.44)	-.1724* (-12.88)	
Percent Wholesale Employment (WHOLE)		-.0436* (-2.24)		-.0411* (-2.06)
Percent Retail Employment (RETAIL)		-.0774* (-2.04)		
Constant	-.4738* (-1.30)	.7233 (1.80)	.7300 (1.87)	.1920 (0.47)
Number of Urban Areas	87	87	87	87
Number of Years	28	28	28	28
Number of Total Obs.	2436	2344**	2422**	2361**
R-squared	0.5348	0.3251	0.3736	0.5339
Degrees of Freedom	2314	2218	2299	2238

Numbers in parens are t-statistics
** Represents statistical significance at the 5% level*
***Smaller number of observations due to missing observations from BEA employment statistics*

For private sector employment, we look at Column (D) and observe that CON has a coefficient of .0332, meaning that a 10% increase in the percentage of an urban area's work force that is employed in the construction industry corresponds to a 0.3% increase in VMTPC. The same change in WHOLE corresponds to a decrease in VMTPC of about 0.4%, possibly due to the wholesale sector's comparatively less vehicle intense production, distribution and sales processes, and location in the periphery of an urban area.

POLICY IMPLICATIONS AND FUTURE RESEARCH

This study provides a careful analysis of the determinants of driving, as measured by vehicle-miles per capita, VMTPC, using a panel data set of 87 urban areas in the U.S. We find that there are significant differences in VMTPC across urban areas as indicated by urban area-specific fixed effects. Further analysis indicates that urban areas with larger urban populations have higher VMTPC and that urban areas in the western part of the U.S. have higher VMTPC than those in other regions of the country.

After correcting for endogeneity issues, we find that urban density significantly reduces VMTPC in only two of our model specifications. This differs from previous literature, which has found the density measure to have a negative and significant impact on VMT under all OLS and 2SLS model specifications (Noland and Cowart 2000). This illustrates the importance of including other important VMT determinants such as the use of alternative modes, including transit and the employment /industry mix of the urban area in the analysis.

One problem with the DENSITY variable is that it is defined for the total urban area, whereas actual densities may vary considerably across the urban area. Although this is the only measure of density available for this data set, household level data might be used in the future to further explore this issue. Since urban form is something that evolves slowly over time, policymakers need to seriously consider policies that promote urban density as part of long-range planning, but given the mixed results here, further investigation of role of the complex relationship between land use (DENSITY) and road use is needed.

Increased transit ridership is found to be significantly associated with lower VMTPC, a finding consistent across all model specifications and also with a priori with expectations. This suggests that development of transit systems can play an important role in VMTPC reduction. However, research is needed to be able to target transit investments toward places where there is the most potential for diversion from auto ridership if this is going to be most effective in VMTPC reduction. Also, future studies that distinguish between bus and light rail ridership could help policymakers with investment decisions regarding transit.

Most interesting are the findings here that suggest the employment mix and industry mix of urban areas may have a significant impact on VMTPC reduction policies. In areas with more public employment relative to private employment, VMTPC appears to be higher. More research needs to address the reasons for this large and significant impact of public employment on VMTPC if successful VMT reduction policies are to be implemented.

Our results show that there can be significantly different impacts on VMTPC depending on the private industry mix in an urban area. Construction employment is found to increase urban area-level VMTPC, whereas wholesale employment appears to result in lower VMTPC. Further delving into the VMTPC requirements of different industries is an important subject for future research. This study provides preliminary evidence that it may be necessary to develop different policies depending on the local industry mix of an urban area, especially if short-run impacts could adversely impact local industries that have high VMT requirements and few viable substitutes for driving.

Due to data availability, options for VMT reduction such as carpooling were not considered here. In particular, an urban area may have fewer vehicle miles per capita if there is effective carpooling taking place. For policy planning purposes it would be useful to know whether such policies have a significant impact on VMTPC as these policies can be relatively low cost. Studies using household survey data might be able to address this question in the future.

Finally, in all the model specifications, the price per mile of driving has a significant and negative impact on vehicle miles per capita that is much larger in the long run than the short run, consistent with expectations and results from previous studies. This suggests that pricing will play an important role in VMT reduction strategies.

This study has shown that there are significant factors that determine VMTPC in urban areas and underscores the point that because of difference in these factors across urban areas, any one VMT reduction policy may have a different impact in different places. We provide insight as to the source of those differences, which should help policymakers design region-specific policies that will be more successful in VMT reduction. However, it will probably take a combination of policies to reduce VMT enough to meet the GHG reduction goals set out by legislatures.

APPENDIX A: URBAN AREA POPULATION SIZE AND REGIONAL GROUPINGS

Table A.1: Urban Areas Population Size Groupings (98 TTI Urban Areas)

Group	Population Grouping	List of UAs (alphabetical)
Very Large (vlg)	More than 3 million	Atlanta GA, Boston MA-NH-RI, Chicago IL-IN, Dallas-Fort Worth-Arlington TX, Detroit MI, Houston TX, Los Angeles-Long Beach-Santa Ana CA, Miami FL, New York-Newark NY-NJ-CT, Philadelphia PA-NJ-DE-MD, Phoenix AZ, San Diego CA, San Francisco-Oakland CA, Seattle WA, Washington DC-VA-MD
Large (lrg)	Between 1 and 3 million	Austin TX, Baltimore MD, Buffalo NY, Charlotte NC-SC, Cincinnati OH-KY-IN, Cleveland OH, Columbus OH, Denver-Aurora CO, Indianapolis IN, Jacksonville FL, Kansas City MO-KS, Las Vegas NV, Louisville KY-IN, Memphis TN-MS, Milwaukee WI, Minneapolis-St. Paul MN, Nashville-Davidson TN, New Orleans LA, Orlando FL, Pittsburgh PA, Portland OR-WA, Providence RI-MA, Raleigh-Durham NC, Riverside-San Bernardino CA, Sacramento CA, San Antonio TX, San Jose CA, St. Louis MO-IL, Tampa-St. Petersburg FL, Virginia Beach VA
Medium (med)	Between 1/2 and 1 million	Akron OH, Albany-Schenectady NY, Albuquerque NM, Allentown-Bethlehem PA-NJ, Bakersfield CA, Baton Rouge LA, Birmingham AL, Bridgeport-Stamford CT-NY, Charleston-North Charleston SC, Colorado Springs CO, Dayton OH, El Paso TX-NM, Fresno CA, Grand Rapids MI, Hartford CT, Honolulu HI, McAllen TX, New Haven CT, Oklahoma City OK, Omaha NE-IA, Oxnard-Ventura CA, Poughkeepsie-Newburgh NY, Richmond VA, Rochester NY, Salt Lake City UT, Sarasota-Bradenton FL, Springfield MA-CT, Toledo OH-MI, Tucson AZ, Tulsa OK, Wichita KS
Small (sml)	Less than 1/2 million	Anchorage AK, Beaumont TX, Boise ID, Boulder CO, Brownsville TX, Cape Coral FL, Columbia SC, Corpus Christi TX, Eugene OR Greensboro NC, Jackson MS, Knoxville TN, Laredo TX, Little Rock AR, Madison WI, Pensacola FL-AL, Provo UT, Salem OR, Spokane WA, Stockton CA, Winston-Salem NC, Worcester MA

Each population size grouping includes 15, 30, 31, and 22 urban areas respectively from largest to smallest.

Table A.2: Urban Areas Regional Groupings (98 Urban Areas)

Group	List of UAs (alphabetical)
Western	Albuquerque NM, Anchorage AK, Bakersfield-Delano CA, Boulder CO, Colorado Springs CO, Denver-Aurora-Broomfield CO, Eugene-Springfield OR, Fresno CA, Honolulu HI, Las Vegas-Paradise NV, Los Angeles-Long Beach-Santa Ana CA , Oxnard-Thousand Oaks-Ventura CA, Phoenix-Mesa-Glendale AZ, Portland-Vancouver-Hillsboro OR-WA, Riverside-San Bernardino-Ontario CA, Sacramento-Arden-Arcade-Roseville CA, Salem OR, Salt Lake City UT, San Diego-Carlsbad-San Marcos CA, San Francisco-Oakland-Fremont CA, San Jose-Sunnyvale-Santa Clara CA, Seattle-Tacoma-Bellevue WA, Spokane WA, Tucson AZ.
Central	Atlanta-Sandy Springs-Marietta GA, Austin-Round Rock-San Marcos TX, Beaumont-Port Arthur TX, Birmingham-Hoover AL, Brownsville-Harlingen TX, Cape Coral-Fort Myers FL, Corpus Christi TX, Dallas-Fort Worth-Arlington TX, El Paso TX, Houston-Sugar Land-Baytown TX, Jacksonville FL, Kansas City MO-KS, Laredo TX, Little Rock-North Little Rock-Conway AR, Miami-Fort Lauderdale-Pompano Beach FL, Minneapolis-St. Paul-Bloomington MN-WI, New Orleans-Metairie-Kenner LA, Oklahoma City OK, Omaha-Council Bluffs NE-IA, Orlando-Kissimmee-Sanford FL, Pensacola-Ferry Pass-Brent FL, San Antonio-New Braunfels TX, St. Louis MO-IL, Tampa-St. Petersburg-Clearwater FL, Tulsa OK, Wichita KS
Eastern	Akron OH, Albany-Schenectady-Troy NY, Allentown-Bethlehem-Easton PA-NJ, Baltimore-Towson MD, Boston-Cambridge-Quincy MA-NH, Bridgeport-Stamford-Norwalk CT, Buffalo-Niagara Falls NY, Charleston-North Charleston-Summerville SC, Charlotte-Gastonia-Rock Hill NC-SC, Chicago-Joliet-Naperville IL-IN-WI, Cincinnati-Middletown OH-KY-IN, Cleveland-Elyria-Mentor OH, Columbia SC, Columbus OH, Dayton OH, Detroit-Warren-Livonia MI, Grand Rapids-Wyoming MI, Hartford-West Hartford-East Hartford CT, Indianapolis-Carmel IN, Knoxville TN, Louisville-Jefferson County KY-IN, Memphis TN-MS-AR, Milwaukee-Waukesha-West Allis WI, Nashville-Davidson-Murfreesboro-Franklin TN, New Haven-Milford CT, New York-Northern New Jersey-Long Island NY-NJ-PA, Philadelphia-Camden-Wilmington PA-NJ-DE-MD, Pittsburgh PA, Poughkeepsie-Newburgh-Middletown NY, Providence-New Bedford-Fall River RI-MA, Raleigh-Cary NC, Richmond VA, Rochester NY, Springfield MA, Toledo OH, Virginia Beach-Norfolk-Newport News VA-NC, Washington-Arlington-Alexandria DC-VA-MD-WV

Each regional grouping includes 24, 26 and 37 urban areas respectively from west to east.

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Endnotes

1. Previous works have noted difficulty in finding an appropriate instrumental variable, saying "all the variables that may correlate with lane miles also tend to be correlated with VMT" (Noland 2001). Hansen and Huang (1997) also were unable to locate an appropriate instrument for their analysis.

2. Two models are considered in setting up the panel data: random effects and fixed effects. A rejection of the Hausman test confirmed that a random effects estimator is not consistent with the fixed effects coefficients, and is thus not efficient (Dougherty 2007). Additionally, the Breusch and Pagan Lagrangian Multiplier test for random effects confirmed that the model does not meet a primary assumption of a random effects model because the variance of error term "u" does not equal zero (Breusch and Pagan 1980). Thus, a fixed effects model was selected, similarly to Noland (2001), Fulton, et al. (2000) and other papers in the literature on VMT's derived demand.

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The Economic Impact of Increased Congestion for Freight-Dependent Businesses in Washington State

by Justin Taylor, Ken Casavant, Jeremy Sage, Danna L. Moore, and Barb Ivanov

Congestion in the transportation system necessitates select businesses to operate on a less efficient production function. A survey of freight-dependent businesses in Washington State was used to calculate the costs of congestion and economic impact of increased congestion. As these businesses spend more to provide goods, responses suggest consumers would pay 60% to 80% of the increased cost. Primary areas of increased cost were identified as additional trucking and inventory costs. Results identify an additional $8.7 billion in consumer costs for a 20% congestion increase. The economic impact is a loss of $3.3 billion in total output and over 27,000 jobs.

INTRODUCTION

The economic vitality and livability of any state readily depends on reliable, responsible, and sustainable transportation. Maintaining the transportation system at a level that allows for the safe, efficient movement of freight is an essential component. Wasted fuel, lost productivity, and reduced mobility on the urban road network are estimated to cost the nation's network users roughly $85 billion annually (HDR 2009). Congestion alone has been found to cost users roughly $37.5 billion, $10 billion (2000 dollars) of which is attributed to trucking firms and those receiving and shipping freight (Winston and Langer 2006). As impressive in magnitude as this estimate is, reporting the cost of congestion alone is not sufficient to affect public policy at the state level. Instead, transportation agencies need additional knowledge to understand the manner by which industries are impacted by congestion, what their likely response will be to increasing congestion, and the net impact of these industry responses to the economy.

To answer these questions, Washington State Department of Transportation's (WSDOT) Freight Systems Division, in coordination with Washington State University's (WSU) Freight Policy Transportation Institute and the WSU Social and Economic Sciences Research Center (SESRC), designed and implemented a cost of congestion study, with a goal of providing WSDOT with specific information about the impacts of congestion on businesses dependent upon goods movement, and how these impacts are subsequently felt through the state's economy (Taylor et al. 2012).

REVIEW OF LITERATURE

Typically, economic impact studies report how an economy changes when an external source of funds moves into a regional economy (e.g., a new manufacturing plant locates in a town, or a highway is constructed or improved). The literature on the mechanisms by which the construction of, or investment in, highways produces economic shocks to the regional economy is extensive and largely identifies the short-term impacts generated by the construction activity itself (Stephanedes 1989; Babcock et al. 2010; Babcock and Leatherman 2011) as opposed to the longer-term employment and output changes, which are often demonstrated to be minimal at best (Stephanedes and Eagle 1987) and generally not uniform in effect (Peterson and Jessup 2008). Adding context to potential for economic development following an investment in new highway infrastructure, Chandra and Thompson (2000) find certain industries grow following investment, while others have more ambiguous outcomes and each witness spatial allocation implications.

Contrary to the consideration of investing in new infrastructure as a component of economic development, congestion is somewhat unique in that “new” money is not being injected into the economy. Instead, congestion causes freight-dependent businesses to operate less efficiently. In other words, they operate on a different, less efficient production function. Highway congestion often acts as a mitigating factor of the achievable benefits of agglomeration in urban areas, particularly in relation to firms that are heavily dependent on truck transportation (Weisbrod et al. 2001). Allen et al. (1994) highlight that given the trucking industry’s rather competitive structure, it may be assumed that much of any cost reduction resulting from an infrastructure improvement will be passed on to the shippers. These effects are subsequently felt throughout the regional economy. The function served by freight transportation in the economy and the suggested transmission of any cost reductions to shippers, who are the direct consumers of freight services, motivates a need for a regional economic framework. Freight movement enables trade networks between industries and their market locations. Improvement to the routes reduces travel cost and thus production costs of goods, as well as reducing uncertainties and risk that come with unreliable delivery. These combine to increase industrial productivity (Weisbrod 2007). Increases to the efficiency of a freight network then produce positive effects felt via job creation and economic activity (Allen et al. 1994; FHWA 2001a, 2001b, 2001c; Weisbrod 2007).

While it is often speculated or assumed that investments in transportation infrastructure contribute to economic growth and increased productivity (FHWA 2004), the actual measurement of such a response resulting from a specific investment in a component of the system is often difficult to establish (Peters et al. 2008), and its full implementation is thus often underdeveloped or overlooked entirely. Improvements via investments in transportation infrastructure that seek to minimize the barriers to travel have an effect of shrinking space and time (Lakshmanan 2011). Subsequently, carrying an analysis forward only at the level of a benefit cost analysis (BCA) may prove insufficient by not establishing the expanded “network” effects felt by freight dependent and other service-based sectors that rely on the services obtained on the transportation network. Peters et al. (2008) suggest that the individual parts of a transportation system may not capture its true economic value, and as such, the best measure may be one of the overall network quality. Additionally, Munnell (1990) found that a state’s investment in public capital has a significant impact on the state’s private employment growth. Thus, in an approach identifying and accounting for economic impacts beyond the direct benefits, analysts may more fully capture the produced externalities of the infrastructure investments not captured by the BCA (Munnell 1990; Nadiri and Mamuneas 1996, 1998; NCHRP 1998; FHWA 2004). It is in this type of approach that transportation benefits (or costs) are transferred to economic impacts via labor, market, business and trade development, as well as increases in Gross Domestic Product (GDP) or Gross Regional Product (GRP) other organizational changes (Lakshmanan and Anderson 2002; Lakshmanan 2011), and logistics reorganization (FHWA 2004).

In this light, and in the growing legislative demand for performance-based investment prioritization (e.g., MAP-21), regional transportation agencies and several state departments of transportation have sought economic frameworks to capture the economic impacts in terms of employment, gross state product, and personal income, in addition to transportation performance benefits (Kaliski et al. 2000; FHWA 2002; EDRG 2008; Kansas DOT 2010; North Carolina DOT 2011). The Texas Transportation Institute’s (TTI) Urban Mobility Report (UMR) shows roughly a tripling of the annual hours of delay per commuter from 1982 to 2005 in cities of all sizes, with only slight relief during the recent recession. The most recent versions of the UMR have begun to attempt to account for the incorporation of urban truck delay, realizing that trucks experience delay and accrue costs differently than do commuter vehicles. Via their directed consideration of truck delay, the researchers identify that despite making up only 7% of the vehicle traffic, truck delays account for 22% of congestion costs in 2011 (Schrank, Eisele, and Lomax 2012).

While TTI and many of the above cited works develop operable mechanisms to explore the benefits (e.g., through performance measure calculations such as travel delay and wasted fuel costs) and economic impacts that are generated from an infrastructure investment or system of investments, little has been explored to understand (via stated preference) the responses of freight-dependent businesses to the potential for facing increasing congestion. Therefore, to explore fully the relationship between congestion, associated costs to industries, and the ripple effects to the state's economy, a new set of data and industry relationships was needed. Prior to this study, the effects of congestion as stated by freight-dependent industries in Washington State had not been measured. Therefore, the results here provide the WSDOT essential new information to respond to the impact of congestion in the state. Additionally, the process developed and employed for Washington provides a replicable process to implement in other states or regions.

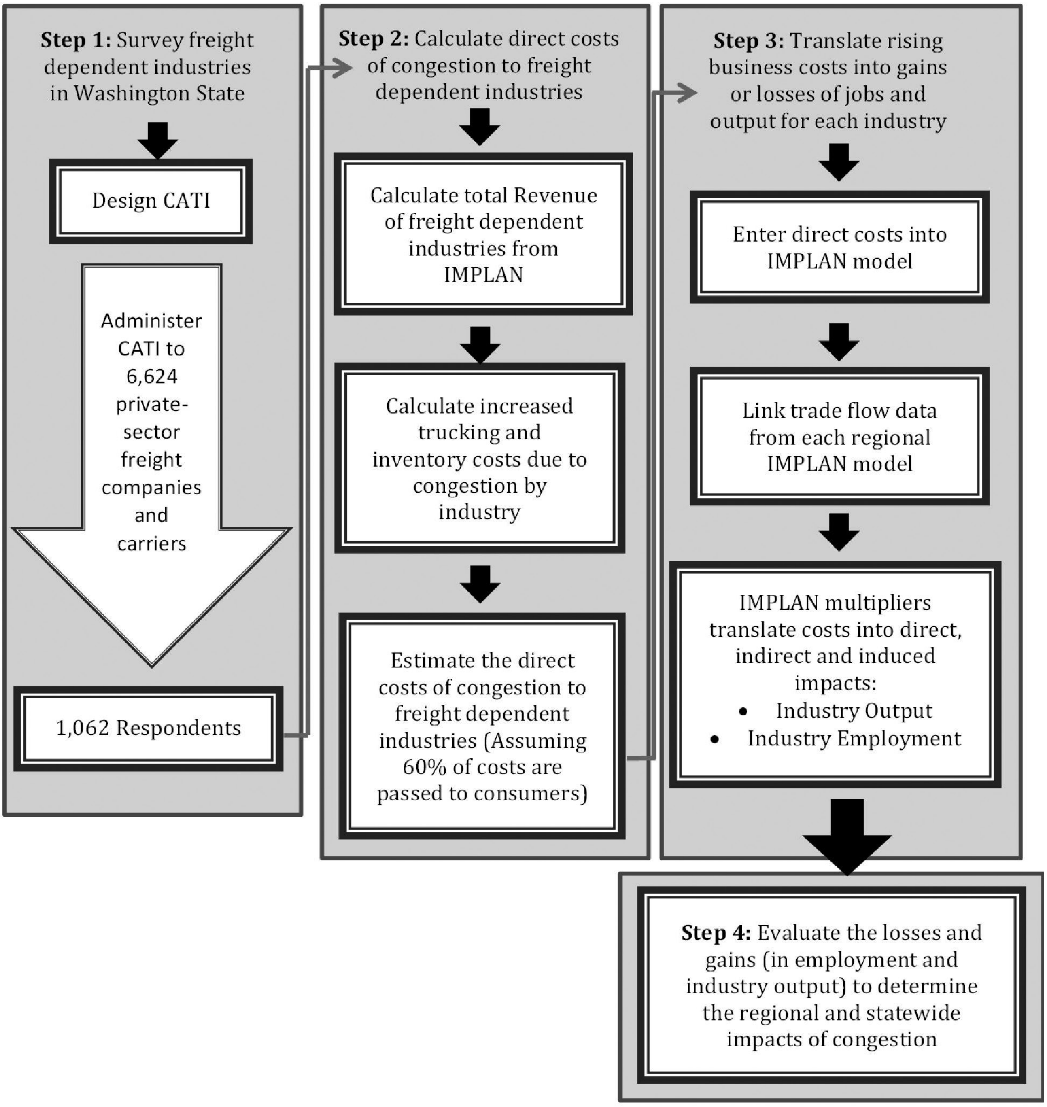
METHODOLOGY: DEVELOPING AN IMPACT ASSESSMENT

To generate data on the relationship between congestion, cost to industries and the state's economy, a four-step methodology was developed, beginning with an extensive survey of freight-dependent businesses. Survey results were then used to obtain a direct cost of congestion to freight-dependent industries. The direct costs were subsequently used as inputs to a series of regional and statewide IMPLAN I-O models (Figure 1).

Step 1. Survey of Freight Dependent Industries

A survey of freight-dependent businesses[1] was conducted by WSU's SESRC (Social and Economic Sciences Research Center) through a developed Computer-Assisted Telephone Interview (CATI) protocol and administered between 2009 and 2011. A total of 6,624 private-sector freight companies and carriers were invited to take the CATI, representing industries from agribusiness, construction, global gateways (e.g., ports), food manufacturing, manufacturing, retail, trucking warehousing, wholesale, and lumber companies. An initial sample of 2,500 cases were drawn from the population by randomly selecting 1,000 trucking companies and then proportionately sampling among the remaining industries with oversampling in the smaller industries so a minimum of 60 cases were drawn from each of the 10 sectors. Respondent industries were grouped in accordance with their two-digit NAICS codes to make them compatible with the IMPLAN aggregation used in later stages. The surveyors recorded completed surveys from 1,062 businesses (29.6% after accounting for the eligibility factor). Questions were formulated to gather data necessary to input into the economic assessment tool, including queries about industry classification, main freight activity, average hourly trucking costs, trucking cost components (e.g., wages, fuel), inventory carrying costs, and strategies to combat congestion. Respondents were asked to identify and direct their responses to the region of the state where they face the most congestion or where the majority of their shipments occur. The identified region was then used to provide context for the remainder of the survey questions. Six Washington State regions were provided as response options: Northwest, Southwest, Central basin, Northeast, Southeast, and Central Puget Sound Metro Area (Table 1). The key component of the survey asked respondents a series of questions regarding how they would react if their travel time increased by 20%, 30%, and 40% due to congestion. Even at the lowest level of congestion increase, a majority of respondents (58%) indicated that the addition of at least one more truck would be included as a component of their strategy to combat the congestion increase. Additional qualitative comments provided by respondents highlight the interaction of additional trucks with other strategies such as longer operating hours, adjusted delivery times, adjusted delivery routes, among others. Thematically, the comments tended towards the development of strategies to avoid the potential loss of customers and business. This theme highlights that, despite being slowed, the firms still need to deliver their mostly contracted shipments. As an example, slower movement may likely lead to a condition in which the four trucks that had previously fully served the firm's contract, can no longer effectively do so, and they must either fail to satisfy the contract or hire an additional

Figure 1: Economic Impact Assessment Methodology



Source: WSDOT, The Impact of Truck Congestion on Washington State's Economy, Executive Summary.

Table 1: Number of Observations by Congestion Region

Congestion Region	Number of Observations
Northwest	267
Southwest	100
Central Basin	99
Northeast	84
Southeast	75
Central Puget Sound	239
Missing	198
Total	1062

truck (driver) to satisfy the demand. This is not an either-or scenario, but one in which respondents suggested it to be a major piece of a reasonable strategy.

Step 2. Direct Costs of Congestion

The increased truck needs were translated into cost information using respondent-provided hourly trucking costs. Hourly trucking costs were annualized by multiplying the hourly rate by 2,080 hours per year. For example, if hourly trucking costs for an additional heavy truck is $76, then the yearly operating cost for the truck is calculated as: (2,080hrs)x($76/hr) = $158,080.The annual cost of operating a truck was then multiplied by the number of trucks necessary to combat the various congestion increases as identified by the survey respondents. Each company's total trucking cost due to increased congestion was then normalized by their reported annual revenue to calculate the percentage trucking cost increase. The annual cost of operating a truck was then multiplied by the number of trucks the respondents said would be necessary to combat 20%, 30%, and 40% congestion increases. Each company's total trucking cost due to increased congestion was then normalized by their reported annual revenue. To calculate state and regional mean trucking cost percentages, the individual companies' percentages were analyzed for outliers. Observations with a trucking cost percentage greater (or less) than two standard deviations from the industry mean were considered outliers and removed from the data before any additional processing was conducted. State level trucking cost percentages were calculated as the mean of all observations, by industry. Similarly, regional means were calculated by region and industry. Any regional industry means that comprised less than three observations or did not exist in the survey dataset were supplanted with the industry state level mean.

A series of survey questions asked respondents if they held inventory and the value of those goods. This series prompted the respondent to estimate how much more inventory would need to be held if congestion levels increased. It was assumed that companies that do not currently hold inventories will not be induced to hold inventory to combat congestion. Respondents were asked to identify their inventory carrying cost as a percentage of inventory value and the components of that carrying cost. The total value of inventory was first divided by the number of days of inventory held to calculate a daily inventory value. The number of additional days of inventory was multiplied by the daily inventory value and the carrying cost percentage to calculate the inventory cost due to congestion. The inventory and the trucking cost percentages from survey respondents that measure the increased costs due to congestion provide an integral component for the calculation of the economic shock created by congestion.

Step 3: Cost Realization

Survey respondents were asked what strategies their companies would employ if travel times permanently increased by 20%. These responses provided insight to how individual businesses would manage increased congestion and the resulting costs. More than half the respondents indicated that they would continue their current operations and pass the costs on to consumers, and another 20% said the additional costs would be absorbed by the company. Two other groups of firms indicated that they would modify their business operations to manage the travel time increases; 16% would change routes and 3% would relocate. Finally, 6% reported that they would go out of business.

These responses can be further analyzed to describe the range of costs that consumers might face due to increased congestion. First, while individual firms might go out of business, their consumers will likely still exist. Therefore, it can be assumed that they will be provided goods from other firms that still face congestion costs. Second, altering business operations to manage increased travel time is not free of costs. Firms will only incur these costs to the point where profits are equivalent to employing the other strategies. Uncertainty about costs from firms that alter their business operations makes it infeasible to calculate exact costs to consumers from congestion. Therefore, all the results are presented at 60% cost realization [for 80% cost realization evaluation, see (Taylor et al. 2012)]. In other words, consumers could likely expect to pay 60% of the increased cost of congestion. The 60% estimate is generated by survey responses. In responding to questions regarding cost management, 60% of respondents indicated that they would pass on the costs of increased congestion to consumers, while 20% said they would absorb the costs, and the remaining 20% indicated an alteration of business operations. Subsequently, assessments were conducted in the model at both the 60% cost realization and the 80%. It is important to note here that this analysis takes a snapshot view of the increased cost of congestion, thus not considering the more long-term effects of the potential of freight consumers to switch transportation modes, thus affecting the overall impact on consumers, or make other such long-run adjustments that enable a more elastic scenario development. The consumers' cost of congestion for freight-dependent businesses, however, does not provide a complete measure of the economic shock. How businesses spend resources to combat congestion must be considered as well.

Traffic congestion occurs when traffic demand approaches or exceeds transportation capacity. Freight-dependent businesses are not able to control the capacity of the transportation system, so they must develop strategies to avoid congestion and/or employ resources to offset its effects. Economic theory suggests that businesses will allocate resources optimally to maximize profits. This optimal allocation of resources specifies a production function. When faced with congestion, firms must reallocate resources and operate on a different and less efficient production function.

Step 4. Economic Costs and Benefits

The cost of congestion is modeled two ways simultaneously. The first value is negative to simulate the decrease in purchases of services and non-freight dependent goods by consumers (consumer cost). The second value is positive and simulates freight-dependent businesses adding employment and assets to combat congestion (societal benefits). The economic impacts that result from these two offsetting impacts are the net impacts of increased congestion for freight-dependent businesses. As indicated in the previous section, congestion is modeled here as the necessary operation on a less efficient production function. This results in what may be a counterintuitive outcome. Freight-dependent industries, as with all industries, seek to operate on the most efficient production function feasible. This often does not coincide with the production levels that maximize output or employment. We identify societal benefits as increases in employment and output. While the employee who now has a job as a result of the congestion, and the manufacturer of the added assets that may view this as a benefit, the firm itself would have preferred to operate on the higher profiting and more efficient production function. Thus, while we identify several industries as experiencing societal benefits, this does not indicate their preferred state.

Before gross congestion costs can be separated into cost and benefit categories, the costs incurred due to exported state goods must be examined. From the consumer cost perspective, the costs attributable to exports do not belong in the state or regional I-O models. If firms are able to pass the congestion cost on to consumers, these costs would be paid for by consumers who do not live in Washington State. From a societal benefit perspective, the inclusion or exclusion of these costs is not as clear. This uncertainty primarily comes from the elasticity of demand for the exported goods. It could be argued that firms would be less capable of passing along congestion costs to export customers because their demand for these goods is more price elastic than for in-state consumers. Furthermore, if firms are not able to increase export prices, it is feasible that in-state consumers would be charged even higher rates. Due to the uncertainty of the existence or direction (i.e., cost or benefit) of congestion costs attributable to exported goods, they were subtracted from the gross congestion costs for consumer costs and societal benefits. Therefore, the costs and benefits used in the I-O models are those paid by consumers and spent by freight-dependent businesses in Washington State.

Additional considerations resulting from the inclusion of inventory adjustments by firms must also be addressed before applying them to either or both of the cost or benefit side of the model. Three components involving inventory should be considered. First, obsolescence and pilferage are legitimate expenses for firms, but they do not garner benefits to society. Second, taxes are transfers from businesses and households to government. These dollars are used to provide non-market goods and services and do not circulate through the economy like spending in other economic sectors. This is not to say that government spending, such as defense expenditures, does not have a multiplier effect. Rather, we consider the model as a point in time and thus future reinvestment via government spending is not accounted for in the year of analysis. Therefore, all three of these components are included in the consumer cost calculations, but are excluded from the societal benefit calculations.

In regional I-O modeling, it is necessary to know the size of the direct costs and where they are accrued. This spatial component applies to consumer costs and societal benefits. Since congestion costs have been limited to those paid and spent in Washington State, there is no real distinction to be made for the state-level model. However, this is a critical step to understand how different regions of the state may be affected by congestion.

Trade flow data from IMPLAN specify the value of exports from one region to another. By linking all the regional models within Washington, an industry-level map of the interregional transfers (“trade” between regions of Washington) was created. Augmenting this information with the total production and export data (also from IMPLAN) provides a complete picture of where goods from each region are shipped. This distribution of production was transformed from values to percentages and used as a roadmap (trade flow matrix) for assigning consumer costs and societal benefits to the region where they would be accrued.

The consumer costs and societal benefits of congestion are entered into the I-O models as changes to the baseline economy. Additionally, the models require that a pattern of spending be specified to define what industries are affected by the change and by how much. The following sections discuss how all of the cost categories were incorporated into the regional and state I-O models.

Consumer Cost. Consumers’ income must increase or their total expenditures must decrease for them to pay the increased cost of freight-dependent goods. Assuming that consumers’ income is held constant, the amount spent on services and non-freight-dependent goods must decrease by the cost of congestion. The household consumption function from IMPLAN was modified to incorporate the spending decrease into each regional or statewide model, while simultaneously accounting for the societal benefits described in the following section.

The household consumption function specifies the percentage of a consumer’s dollar that is spent in each industry in the economy. Furthermore, it shows how much of that industry expenditure is spent in the local economy. The magnitude of the industry-specific consumer expenditures in these consumption functions varies depending on the household’s income level and the region. We do not have information on which households will incur congestion costs; therefore, a composite consumption function was created for each region.

The composite function was calculated as a weighted average industry expenditure for all income ranges. The number of households in each income range was used for weighting. The composite consumption functions were then modified to remove all freight-dependent industries and normalized to sum to one. Finally, scenarios (based on 20%, 30%, and 40% congestion increases) were created in each model with the composite consumption function and the corresponding consumer costs.

For the regionally constructed models, the congestion costs for each regional industry were multiplied by the trade flow matrix to assign the appropriate congestion cost values to each region.

State level costs were calculated after subtracting the costs attributable to exports. The state and regional consumer cost values at each congestion level were then summed across industries to calculate total consumer costs. The vast majority (95%) of the consumer cost of congestion is attributable to trucking costs.

Societal benefits. Societal benefits occur when freight-dependent companies begin to spend additional money on resources to counteract increased congestion. For modeling purposes, adding societal benefits to the economy is straightforward. Spending on insurance and capital is placed in the corresponding IMPLAN industries. Wages are modeled as an increase to employee compensation.

Warehousing and trucking input expenditures are not discrete goods, therefore, existing consumption functions were used to estimate the distribution of expenses across industries. To model warehousing expenditures and trucking input expenditures, the “warehousing and storage consumption function” and “the transport by truck industry consumption function” were used. Scenarios for each congestion level were created in each model using the appropriate consumption function and expenditure values.

Societal benefits are accrued in different regions of Washington based on where the expenditures will be made. Trucking expenses (i.e., wages and inputs) are presumed to be spent in each firm’s home region. Capital and insurance inventory costs are also accrued in the home region. Warehousing, handling, and clerical expenses to freight customers are accrued in the destination regions. Handling and clerical expenses are considered to be inventory wage expenses. State level benefits were calculated after subtracting the costs attributable to exports. The state and regional societal benefit values at each congestion level were then summed across industries to calculate total consumer costs (Table 2).

Table 2: Net Effect of Consumer Cost and Societal Benefit

	Societal Benefits	Consumer Cost	Net Effect
Northwest	$ 839,777,837.00	$ 786,951,341.00	$ 52,826,496.00
Southwest	$ 726,634,062.00	$ 764,545,407.00	$ -37,911,345.00
Central Basin	$ 535,672,497.00	$ 588,952,830.00	$ -53,280,333.00
Northeast	$ 497,611,946.00	$ 498,958,368.00	$ -1,346,422.00
Southeast	$ 209,026,349.00	$ 193,562,034.00	$ 15,464,315.00
Puget Sound	$ 6,847,315,653.00	$ 7,052,246,826.00	$ -204,931,173.00
State	$ 8,529,297,034.00	$ 8,720,889,371.00	$ -191,592,337.00

Net effects. The net economic impacts are calculated through the I-O models, and the net effects are provided in Table 2 for illustrative purposes. Juxtaposing the societal benefits and consumer costs from congestion by region shows the range in the effects. The Northwest and Southeast regions have benefits in excess of their consumer costs. The deficit in the other regions ranges from $1.3 million in the Northeast to $205 million in Puget Sound. The net effects presented here differ from the economic impacts because they do not account for how the industries or households spend or withdraw money in the local economies.

RESULTS

The strength of an I-O model comes from the vast amount of data that it contains to describe how industries and institutions in an economy interact. These interactions allow the model to estimate the full impacts from a change in the economy. The direct costs are entered into the model as the changes to the primary industries (specified in the spending patterns). Multipliers are then used to calculate the direct, indirect, and induced impacts. Direct impacts are a measure of how the local economy is affected by changes to the primary industries. Indirect impacts are the changes that would occur in the industries that support the primary industries. Induced impacts quantify the economic changes that result from household incomes being altered in the direct and indirect phases.

In this case, freight-dependent industries spend money on employees and inputs when transporting and storing goods to counteract increased congestion. This money is spent on goods that are supplied by local purveyors or imported. In turn, the local purveyors spend additional money on employees and inputs from inside and outside the local economy. Employees of the freight–dependent industries and the purveyors also spend their additional income on goods and services from the local economy or imports. All this additional spending is financed by in-state consumers who are paying higher prices for freight-dependent goods and decreased profits.

The remainder of this paper discusses the economic impact estimates from increased congestion in Washington State. The estimates are annual figures in 2011 dollars and are based on 2008 IMPLAN datasets for Washington State and six regions of the state.

Statewide Model

There are several measures that can be used to illustrate economic impact. Table 3 presents three of the most common measures for a 20% congestion increase in Washington. Employment is a straightforward metric that shows the number of full- and part-time jobs affected by increased congestion for freight-dependent businesses. The net employment effect of a 20% congestion increase is a decrease of 27,256 jobs (0.7%). The value of economic output from the state decreases by $3.3 billion (0.5%). Total value added (sales minus cost of inputs) also decreases by $2.6 billion (0.8 %).

Table 3: Summary Impact, 20% Congestion Increase

Impact Type	Employment	Value Added	Output	Percentage Change		
				Employment	Value Added	Output
Direct Effect	-49,033	-$4,259,110,941	-$7,051,171,371	-1.30%	-1.30%	-1.10%
Indirect Effect	11,146	$754,724,562	$2,167,768,066	0.30%	0.20%	0.30%
Induced Effect	10,631	$894,924,391	$1,568,440,631	0.30%	0.30%	0.20%
Total Effect	-27,256	-$2,609,461,988	$3,314,962,675	-0.70%	-0.80%	-0.50%

As congestion increases to 30% and 40% levels, the losses increase substantially. An additional 10% congestion increase causes job losses of 40,859 and output to decrease by $4.9 billion (a 48.5% increase) (Taylor et al. 2012). A further 10% congestion increase would cut 57,239 jobs and decrease output by $7 billion (a 42.9% increase) (Taylor et al. 2012). The magnitude of all the economic impacts from congestion increases is large. However, the changes relative to the industry totals are reasonable.

Table 4 shows the total impact for each industry in the state and the percentage change from their baseline employment and output. Almost half (10 to 11) of the industries have a change in employment and output of plus or minus 1%. The industries losing the most jobs, in percentage terms, are health and social services, educational services, and arts-entertainment-recreation. The 60% cost realization job losses in these industries range from 3.4% to 4.5%. These three industries also have the greatest percentage losses in output value, 4.1% to 4.9%.

Table 4: Total Impact by Industry, 20% Congestion Increase

Industry	Employment	Output	Employment	Output
Ag, Forestry, Fish & Hunting	-1	$281,859	0.00%	0.00%
Mining	67	$30,221,017	1.30%	1.80%
Utilities	-111	-$83,024,003	-2.10%	-2.00%
Construction	-516	-$63,877,436	-0.20%	-0.20%
Manufacturing	243	$1,266,264,942	0.10%	0.80%
Wholesale Trade	861	$173,828,805	0.60%	0.60%
Retail Trade	2,678	$237,128,393	0.70%	0.70%
Transportation & Warehousing	8,595	$1,040,011,974	7.60%	6.20%
Information	-852	-$351,819,756	-0.70%	-0.60%
Finance & Insurance	-2,403	-$601,477,474	-1.70%	-1.70%
Real Estate & Rental	-4,566	-$2,012,319,651	-2.50%	-3.60%
Professional-Scientific & Tech Svcs	-1,252	-$153,672,541	-0.50%	-0.40%
Management of Companies	169	$46,157,877	0.50%	0.60%
Administrative Services	4,062	$237,267,293	2.30%	2.00%
Waste Management	-38	-$9,805,661	-0.30%	-0.30%
Educational Svcs	-2,236	-$134,253,839	-3.60%	-4.10%
Health & Social Services	-16,130	-$1,668,845,334	-4.50%	-4.90%
Arts- Entertainment & Recreation	-2,795	-$252,897,663	-3.40%	-4.10%
Accommodation & Food Services	-7,812	-$503,159,853	-3.20%	-3.30%
Other Services	-6,376	-$404,962,415	-3.00%	-2.80%
Government & non NAICs	1,156	-$106,009,207	0.20%	-0.20%
Total	-27,257	-$3,314,962,673	-0.7%	-0.5%

These results are understandable considering that health and social services expenditures are almost entirely local (84%) and it is the largest non-freight-dependent household expenditure category, second largest overall (Taylor et al. 2012). The educational services and arts-entertainment-recreation expenditures are highly localized as well (63% and 83%, respectively). These industries, however, are two of the smallest based on employment and output. Therefore, any decrease in household expenditures for these industries has a large effect.

Seven industry sectors (in addition to the government sector) had positive changes to their employment. Administrative services and transportation and warehousing are the only industries with employment job changes greater than 2% (2.3% and 7.6%, respectively). Transportation and warehousing was the only industry with output values increasing by more than 3%. The gains to freight-dependent industries were expected as more resources are devoted to the transportation of goods to combat congestion. The only freight-dependent sectors with losses are the agriculture and construction industries. The agriculture industry losses are negligible; however the construction industry losses are not. This loss is largely attributable to the industries interdependence with the real estate and rental industry. The real estate and rental sector receives the third largest proportion of household expenditures (17%) and 95% is spent locally. Two non-freight-dependent industries, administrative services and management of companies, show positive changes from increased congestion. Both of these industries provide support services for businesses and benefit from the increased expenditure by freight-dependent businesses.

As congestion levels increase to 30% and 40%, the magnitude of the impacts also increases (Taylor et al. 2012). The relative order of industries being affected by congestion does not change. Health and social services continues to take the largest losses in jobs (6.8% and 9.6%, respectively) and output value (7.5% and 10.5%, respectively). Similarly, transportation and warehousing gains in employment by 11.7% and 16.4% and output values grow by 9.5 % and 13.4%.

It is important to note that the cost calculations are based on the survey responses and relying heavily on the respondents' ability to forecast cost changes for congestion increases may be erroneous. However, some general comments can be made. As congestion increases, the number of industries negatively affected increases, as does the severity of the losses. For example, at a 20% increase in congestion, 38% of the industries have employment losses greater than 1%; that percentage grows to 43% when congestion increases by 40%. The average negative employment effect for those industries, changes from 3% to 4% up to 6% to 8% as congestion increases from 20% to 40% (Taylor et al. 2012). Correspondingly, the industries that gain from congestion have average employment increases of 5% and 7% to 8% at congestion levels of 20% and 40%, respectively (Taylor et al. 2012).

Regional Model

The trade flow matrix derived from the Washington-regional IMPLAN models contains a vast amount of information on where goods are produced and used. These data allow us to allocate consumer costs and societal benefits in the region where they are accrued. Thus, the magnitude of the congestion impacts varies significantly across the regions. Table 5 shows the total effect of congestion for the three primary metrics in each region. All of the regions are negatively affected by increases in congestion, but the Puget Sound region faces the largest costs in absolute and percentage terms. Their output decrease of $3.6 billion (0.8%) is greater than all other regions combined. The industries affected the most in each region closely follow the state level results (Taylor et al. 2012). At 20% congestion increases, 10 of the industries in each region have total employment and output effects of plus or minus 1% of their baseline levels. For the industries with losses in excess of 1%, the average employment and output effects range from 2% to 4% of the baseline level. Health and social services, educational services, and arts-entertainment-recreation industries consistently have the largest percentage losses in all of the regions. The real estate and rental industry appears in four of the seven regions as the second most affected for output losses. The accommodation and food service industry ranks as the third most affected industry in the Puget Sound and Southeast regions for employment losses.

Table 5: Total Effect, 20% Congestion Increase, by Region

				Percentage Change		
Region	Employment	Value Added	Output	Employment	Value Added	Output
Northwest	-1,786	-$163,102,595	-$162,360,385	-0.48%	-0.63%	-0.29%
Southwest	-1,622	-$174,475,347	-$265,810,407	-0.52%	-0.79%	-0.57%
Central Basin	-1,793	-$141,465,489	-$244,442,954	-0.47%	-0.61%	-0.54%
Northeast	-2,213	-$162,922,959	-$289,661,584	-0.77%	-0.84%	-0.80%
Southeast	-345	-$27,408,355	-$30,848,239	-0.31%	-0.40%	-0.21%
Puget Sound	-21,741	-$2,305,044,223	-$3,639,269,096	-0.90%	-0.98%	-0.82%
Total	-29,500	-$2,974,418,968	-$4,632,392,665	-0.76%	-0.89%	-0.72%

The administrative services and transportation and warehousing industries consistently have the highest gains from congestion across the regions (20% congestion increases). Wholesale trade and mining industries also appear in at least two regions as one of the top three gaining industries. For the industries with gains in excess of 1%, the average employment effects range from 3% to 6% and output effects range from 2% to 5% of the baseline level.

CONCLUSION

Washington's economic vitality and livability depend on reliable, responsible, and sustainable transportation. Maintaining the transportation system at a level that allows for the safe, efficient movement of freight is an important component of this sustainable system. To this end, the findings of this study suggest several "lessons learned" and recommendations for WSDOT.

Congestion causes freight-dependent businesses, such as manufacturing, retail and wholesale trade, agriculture, construction, and timber/wood products, to operate less efficiently by increasing the amount of time for each truck trip and increasing the time that trucks (and drivers) spend in traffic; thereby, spending time in an unproductive manner. This study estimates that a 20% increase in congestion experienced by commercial trucks would result in over $14 billion of increased operating costs to Washington's freight-dependent industries. Since many freight industries have the ability to pass on their rising transportation costs in the form of higher cost goods, consumers and service industries may feel the biggest impacts from increasing congestion. When multiplied into economic impacts, this translates into losses of over 27,250 jobs (0.70% of statewide total) and $3.3 billion (0.51% of statewide total) in economic output (2011 dollars).

The results suggest that economic impacts of rising congestion will be felt in every region of the state. However, they will be the most acute in the central Puget Sound Metropolitan region. The investment prioritization process should take this into account when selecting the most efficient projects to alleviate congestion. An increase of 20% over today's congestion levels is projected to cause more than 21,700 job losses (0.90% of the Puget Sound regional total), as well as decreased regional output of over $3.6 billion (0.82% of the Puget Sound region's total output). The other five regions in Washington State would see decreased regional output of between $31 million and $290 million (between 0.21% and 0.80% of each region's total output), and would cause each region to lose between 345 and 2,200 jobs (between 0.31% and 0.77% of each region's total jobs).

These demonstrated economic impacts suggest that WSDOT should prioritize investments that enhance mobility for trucks and freight industries as a way to support the state's goals of a strong economy. Washington State law directs public investments in transportation to support economic vitality, preservation, safety, mobility, the environment, and system stewardship. A demonstrated economic link between truck congestion and increased costs to consumers and industry means that WSDOT could prioritize investments to enhance the mobility of trucks.

Endnotes

1. The population for the survey consisted of all businesses registered in the State of Washington and companies in freight-dependent sectors or designated as owning and operating trucks or other freight vehicles in Washington State. The population list sent from the employment security department (ESD) included a total of 83,000 cases. After SESRC removed 9,519 obvious duplicates and substantially incomplete (uncontactable) cases, a total of 73,481 businesses remained.

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Network-Based Simulation of Air Pollution Emissions Associated with Truck Operations

by Joongkoo Cho and Weihong Hu

Estimating greenhouse gases (GHGs) and other emissions (especially diesel particulates) is an increasingly important basis for regional policy analysis. According to the EPA (2010a), the transportation sector contributed 27.2% of total GHG emissions in 2008, and 50% of these were from truck operations. This research focuses on estimating GHGs and other emissions (e.g., PM) from freight movements on roads in California as well as the concurrent effects of various mitigation scenarios. The study demonstrates that interregional freight flow data, along with FAF data can be important data sources for emission models. The results are useful not only for estimating GHGs and other emissions based on estimated freight flows, but also for evaluating area-specific environmental impacts of policy alternatives. The analysis shows that emissions impacts vary by study area as well as by policy. A policy alternative that has a significant impact in a specific area may have a trivial impact in a broader region. Also, an emissions reduction in one area may be because of emissions increases in another area. Therefore, it is important to simulate possible emissions impacts by applying a spatially disaggregated model to help decision makers weigh alternatives. The study can also be applied for analyzing environmental justice when the emission results are disaggregated into small areas.

INTRODUCTION

Motivation

Evaluating a regional transportation plan (RTP) in terms of air quality impacts is now essential for local, state, and federal governments. This is why the U.S. Environmental Protection Agency (EPA) has developed the Motor Vehicle Emission Simulator (MOVES), which is an emissions model at the national and sub-regional levels. The California Air Resources Board (CARB) has developed the Emission Factors (EMFAC) model, which is an emissions model for California. The Center for Environment Research and Technology at the University of California, Riverside, has also developed a Comprehensive Modal Emission Model (CMEM) with sponsorship from the National Cooperative Highway Research Program (NCHRP) and the U.S. EPA.

There are many difficulties associated with developing an emissions model. Useable data are scarce and reliable parameters are hard to judge. Basically, emissions levels are estimated by production of emission factors (e.g., tons per vehicle mile by various speeds) and by vehicle activities (CARB 2007, EPA 2010b). Therefore, researchers have worked on estimating reasonable emissions factor parameters, vehicle activities, or interaction between emissions levels and vehicle activities (Barth and Boriboonsomsin 2009). The EMFAC models have incorporated such research results and have been widely used by government agencies and researchers. The EMFAC model may calculate incorrect emission estimates for a small region such as a traffic analysis zone (TAZ) (Barth 1996), but it is useful for identifying trends of emissions levels for large areas such as counties.

Although EMFAC provides comprehensive data, the key factor, vehicle miles traveled (VMT), are not provided as origin-destination flows, leaving opportunities for policy analysis based on transportation network performance limited. The shortcomings may be resolved by using freight flows that are estimated between specific origin-destination pairs by industry sectors. Therefore, it is expected that consistent sub-state VMT estimates determined via simulation of actual trade flows and consequent use of the road networks would make emissions models much more useful for policy analysis.

Research Objectives

The primary research objective is to simulate air pollution emissions on California road networks associated with truck operations. There are three main procedures of the study. First, truck freight flows are estimated between ZIP code areas. Estimating spatially disaggregated freight flows is essential for this study and ZIP code areas are the most disaggregated spatial units for estimating freight flows by industry sectors. Second, a highway network model is developed to estimate VMT on the network based on the estimated truck origin-destination (O-D) flows. Third, the results from the transportation model are used as inputs to an air pollution emissions model. Various policy scenarios are tested by the developed model.

LITERATURE AND EXISTING MODEL REVIEW

Air pollution emissions caused by transport activities can be grouped into two types: greenhouse gasses (GHGs) and other pollutants. GHGs include Carbon Dioxide (CO_2), Methane (CH_4), and Nitrous Oxide (N_2O) from fuel combustion and F-gases (fluorinated gases) from vehicle air conditioning (Kahn Ribeiro et al. 2007). Other pollutants are Total Gaseous Hydrocarbons (TOG), Carbon Monoxide (CO), Oxides of Nitrogen (NOx), Particulate matter (PM_{10}, $PM_{2.5}$), and Oxides of sulfur (SOx) (CARB 2007; EPA 2010b). Efforts have been made to estimate GHGs and other pollutants caused by transport activities (Benjamin and Long 1995, Cicero-Fernandez and Long 1995). Estimation processes reflect an understanding of which factors affect emissions rates.

In the 1990s, there were several ways to estimate vehicle emission parameters. Equipment such as data-logger or global positioning systems (GPS) were installed to collect data from vehicle operations (Benjamin and Long 1995, Magbuhat and Long 1996). Data were assembled to determine distributions of VMT, trips, temperature, and speed during weekdays and weekends. Grades and other loads effects on emissions were analyzed (Cicero-Fernandez and Long 1995, 1996). Benefits of emission rates data from on-board diagnostics and inspection/maintenance (I/M) were studied (Patel and Carlock 1995). Based on these research results, the California Air Resources Board (CARB) developed an air pollution emissions model called Emission Factors (EMFAC). As mentioned above, VMT provided by EMFAC, a primary input for the model, has limitations for policy analysis. Building a truck O-D matrix is a way to overcome the limitation.

Early studies of truck O-D estimation generally resemble passenger O-D estimation and follow the same methodologies. Gravity models were applied by Meyburg (1976), Swan Wooster (1979), Southworth (1982), Ashtakala and Murthy (1988), and Tamin and Willumsen (1988). Mathematical programming models were applied by Gedeon et al. (1993) and List and Turnquist (1994). Heuristic solution techniques were applied in Tavasszy et al. (1994) and Al-Battaineh and Kaysi (2005). However, it has been widely accepted that freight modeling differs from its passenger counterpart (Holguin-Veras et al. 2001, Wisetjindawat et al. 2006, Hunt and Stefan 2007, Giuliano et al. 2010). Therefore, various approaches have been applied to reflect the unique nature of truck O-D flows.

Truck O-D estimation methodologies can be classified via various criteria. A criterion can be the data involved, which classifies the existing research into two major groups: direct sampling and estimation from secondary data sources (i.e., O-D synthesis) (Cascetta 1984). Direct sampling employs survey data obtained from home interviews, license plate surveys, and roadside surveys to set the parameters of classical sampling theory estimators. The main drawbacks of such techniques are threefold: (1) the variances and covariances of the O-D values depend on the sampling technique and the estimator adopted, and thus may be unstable; (2) bias is often introduced in the parameters due to lack of calibration and systematic errors in survey work; (3) large-scale traffic surveys tend to be time-consuming and labor-intensive, which can be exacerbated by the dynamic nature of transportation demand. In the case of freight modeling, there is also the problem of data reliability because firms may be reluctant to report various operational details.

Estimation from secondary data sources is an effort to derive the desired O-D matrix by matching the cells with observed or available secondary data conforming to predefined rules. Inputs like link volumes (traffic counts) contain the most important information about O-D distributions and can be updated readily when dynamics are taken into account (Réos et al. 2002). This enables such estimation methods to bypass the need for large surveys and, as a result, they appear attractive. Secondary freight flow data generally have three problems: (1) different data sources reveal different aspects of freight flows, but hardly any single source can describe the complete flows regarding an area; (2) they are not equally available for various modes; (3) most are at an aggregate level, whereas the desired analysis requires more disaggregate data.

Giuliano et al. (2010) attempted to address the first two shortcomings of secondary data sources. Their underlying logic estimates regional commodity-specific O-D matrices by integrating international, interregional, and intraregional trip attractions and productions. The authors generated intraregional productions and attractions utilizing a regional input-output transactions table as well as small area employment data.

The Federal Highway Administration (FHWA) attempted to address these three issues in the Freight Analysis Framework (FAF) database. FAF contains 123 domestic regions and eight foreign regions for exports and imports. Forty-three commodity flows transported by trucks and other modes are provided. FAF is constructed based on the Commodity Flow Survey (CFS). For industrial sectors that CFS does not include, alternative data were used to complete the estimation. Those alternative data include Census of Agriculture for farm-based agricultural shipments, fisheries of the United States for fishery shipments, and U.S. National Input-Output Accounts for commodity flows associated with the construction, services, retail, and household and nusiness moves industrial sectors (Southworth et al. 2011). The outputs are freight O-D flows in dollar and ton values among 131 FAF regions by 43 commodity classes and seven modes of transportation. After the FAF data were released, efforts were made to disaggregate the state and Metropolitan Statistical Area flows into sub-state areas (Anderson et al. 2008, Anderson et al. 2010, Rowinski et al. 2008, Opie et al. 2009, Viswanathan et al. 2008, Harris et al. 2009). Estimating truck O-D flows at local areas, however, are still challenging due to data limitations.

Recently, IMPLAN (Impacts for Planning) input-output data at the ZIP code were released. IMPLAN is an economic impact modeling system that provides commodity flows by 440 industry sectors for U.S., state, county, and ZIP code areas. IMPLAN has been applied for estimating economic impacts of government policy (Norton 2011), industry investment (Calcagno et al. 2003), development project (Doublas and Harpman 1995), and household spending (Bergstrom et al. 1990). IMPLAN has also been applied for estimating freight flows between states (Park et al. 2009) and sub-state regions (Giuliano et al. 2010). Data at the ZIP code area level, however, have not been applied for estimating freight flows. Truck trips can be estimated among ZIP code areas when IMPLAN data are combined with FAF O-D matrix and network data. This approach can help local planners and individuals to save time collecting extensive amounts of data. The estimated truck O-D matrix will be useful to analyze various emission reduction policies.

Summary of Literature Review

Methodologies for estimating truck O-D flows can be classified into two major groups: direct sampling and estimation from secondary data sources. Since direct sampling tends to be time-consuming and labor-intensive, estimation from secondary data sources appeared more attractive for truck O-D estimation. Although there have been studies to estimate truck O-D flows at the sub-state level, estimation at small areas such as ZIP code has not been applied due to data limitations. IMPLAN input-output data at ZIP code area along with FAF data can be used to estimate truck O-D flows between ZIP code areas.

METHODS APPLIED IN THIS STUDY

This research presents a method to estimate truck O-D flows among ZIP code areas by using IMPLAN input-output data and FAF data. The estimated O-D flows are then used as an input to estimate truck VMT. The estimated VMT are used as an input to an air pollution emissions model, in this case the EMFAC model for California. Several steps are needed to estimate truck O-D flows between ZIP code areas and consequent air pollution emissions from IMPLAN ZIP code area input-output data and FAF data.

Truck Origin-Destination (O-D) Flows Estimation

Estimating truck O-D flows at ZIP code areas in California and between California and other states is the first step for estimating truck VMT. IMPLAN 2008 ZIP code data are the basis for truck O-D flows estimation. Following are the data provided by IMPLAN for a ZIP code area.

- Total commodity output produced in a ZIP code area and total commodity demand attracted to the ZIP code area.
- Foreign exports and foreign imports by the ZIP code area.
- Local supply, which shows commodities that are produced and consumed at the same ZIP code area.
- Domestic exports of the ZIP code area and Domestic imports into the ZIP code area.

As shown above, IMPLAN provides complete trade flows in a ZIP code area. IMPLAN data, however, do not provide origin-destination flows or mode information, which are necessary to estimate truck O-D flows. Therefore, FAF data are used to obtain O-D and mode information. Table 1 shows a comparison between IMPLAN and FAF. It shows that FAF data provide freight O-D flows and mode information among Metropolitan Statistical Areas (MSA) while IMPLAN provides trade flows at ZIP code areas without O-D or mode information. Tables 2 and 3 show detailed information on O-D flows provided by FAF data. The Los Angeles MSA is chosen as an illustration. Table 2 shows O-D flows of domestic and foreign imports in the Los Angeles MSA. California consists of four MSAs and a remainder. The remainder areas include any regions that are not included in the four MSAs in California. Table 2 shows that the Los Angeles MSA has five origins in California and 118 origins outside California for domestic import. In the case of foreign imports, the Los Angeles MSA becomes a domestic origin to deliver the imported goods to domestic destinations. Table 3 shows export components for which the Los Angeles MSA becomes origins for both domestic and foreign exports.

To apply O-D and mode information from FAF data to IMPLAN data, first, IMPLAN 440 sectors are matched to 43 Standard Classification of Transported Goods (SCTG) commodity sectors based on a bridge between the North American Industry Classification System (NAICS) and SCTG (U.S. DOT FHWA 2009). Second, ZIP code data are aggregated to MSA according to the spatial definitions of FAF. In other words, data for all ZIP code areas in each MSA are aggregated to get freight flows for the MSA.

Table 1: Comparisons of IMPLAN Data and FAF Data

Data	Geography	OD information	Mode Information	Sector	Value
IMPLAN	ZIP code	X	X	440 sectors	Dollar
FAF	MSA	O	O	43 sectors	Dollar/Ton

Table 2: Los Angeles MSA Import Components from FAF Data

Los Angeles MSA Domestic Import		Los Angeles MSA Foreign Import		
Origin	Destination	Foreign Origin	Domestic Origin	Domestic Destination
Los Angeles MSA	Los Angeles MSA	Foreign country	Los Angeles MSA	Los Angeles MSA
Sacramento MSA				Sacramento MSA
San Diego MSA				San Diego MSA
San Francisco MSA				San Francisco MSA
Remainder				Remainder
Other States[1]				Other States

Table 3: Los Angeles MSA Export Components from FAF Data

Los Angeles MSA Domestic Export		Los Angeles MSA Foreign Export		
Origin	Destination	Domestic Origin	Domestic Destination	Foreign Destination
Los Angeles MSA	Los Angeles MSA	Los Angeles MSA	Los Angeles MSA	Foreign country
	Sacramento MSA		Sacramento MSA	
	San Diego MSA		San Diego MSA	
	San Francisco MSA		San Francisco MSA	
	Remainder		Remainder	
	Other States		Other States	

Third, proportions of trades among MSAs and dollar to ton conversion factors are estimated from FAF data. Dollar to Proportions of truck class are also estimated from Vehicle Inventory Use Survey (VIUS) data. Fourth, truck O-D flows by commodity sectors are estimated by multiplying trade flows at MSAs obtained from IMPLAN by trade proportions estimated from FAF. Equation (1) ~ (4) show the calculation process for domestic import, domestic export, foreign import, and foreign export, respectively. Each equation is repeated for all 43 SCTG sectors.

(1) $Trade_{ij}^{T\_DI,k} = IMP_{j}^{DI} \times Prop_{ij}^{T\_DI} \times FAF_{ij}^{DI\_Ton} \times VIUS_{i}^{k}$, $i = 1\sim123, j = 1\sim123, k = 1\sim7.$

(2) $Trade_{ij}^{T\_DE,k} = IMP_{i}^{DE} \times Prop_{ij}^{DE} \times FAF_{ij}^{DE\_Ton} \times VIUS_{i}^{k}$, $i = 1\sim123, j = 1\sim123, k = 1\sim7.$

(3) $Trade_{ij}^{T\_FI,k} = IMP_{i}^{FI} \times Prop_{ij}^{FI} \times FAF_{ij}^{FI\_Ton} \times VIUS_{i}^{k}$, $i = 1\sim123, j = 1\sim123, k = 1\sim7.$

(4) $Trade_{ij}^{T\_FE,k} = IMP_{i}^{FE} \times Prop_{ij}^{FE} \times FAF_{ij}^{FE\_Ton} \times VIUS_{i}^{k}$, $i = 1\sim123, j = 1\sim123, k = 1\sim7.$

Where

$Trade_{ij}^{T\_DI,k}$ is domestic imports by truck mode and ton value by truck class from origin i to destination j,

$Trade_{ij}^{T\_DE,k}$ is domestic exports by truck mode and ton value by truck class from origin i to destination j,

$Trade_{ij}^{T\_FI,k}$ is estimated foreign imports by truck mode and ton value by truck class from intermediate domestic destination i to final destination j,

$Trade_{ij}^{T\_FE,k}$ is estimated foreign exports by truck mode and ton value by truck class from origin i to intermediate domestic destination j to be delivered to foreign countries,

IMP_j^{DI} is the amount of domestic import by dollar value at region j provided by IMPLAN,

IMP_i^{DE} is the amount of domestic export by dollar value from region i provided by IMPLAN,

IMP_i^{FI} is the amount of foreign import by dollar value from region i provided by IMPLAN,

IMP_i^{FE} is the amount of foreign export by dollar value from region i provided by IMPLAN,

$Prop_{ij}^{T\_DI} = FAF_{ij}^{T\_DI} / \sum_{j=1}^{123} FAF_{ij}^{DI}$ is proportion of domestic imports by truck mode from origin i to destination j,

$Prop_{ij}^{T\_FI} = FAF_{ij}^{T\_FI} / \sum_{j=1}^{123} FAF_{ij}^{FI}$ is proportion of foreign imports by truck mode from intermediate domestic destination i to final destination j,

$Prop_{ij}^{T\_DE} = FAF_{ij}^{T\_DE} / \sum_{j=1}^{123} FAF_{ij}^{DE}$ is proportion of domestic exports by truck mode from origin i to destination j,

$Prop_{ij}^{T\_FE} = FAF_{ij}^{T\_FE} / \sum_{j=1}^{123} FAF_{ij}^{FE}$ is proportion of foreign exports by truck mode from domestic origin i to intermediate domestic destination j to be delivered to foreign countries,

$FAF_{ij}^{T\_DI}$ is the amount of domestic import by truck mode from origin i to destination j provided by FAF data,

$FAF_{ij}^{T\_FI}$ is the amount of foreign import by truck mode from intermediate domestic destination i to final destination j provided by FAF data,

$FAF_{ij}^{T\_DE}$ is the amount of domestic exports by truck mode from origin i to destination j provided by FAF data,

$FAF_{ij}^{T\_FE}$ is the amount of foreign export by truck mode from domestic origin i to intermediate domestic destination j provided by FAF data,

$\sum_{j=1}^{123} FAF_{ij}^{DI}$ is the total domestic import at region j provided by FAF data,

$\sum_{j=1}^{123} FAF_{ij}^{FI}$ is the total foreign import at intermediate domestic destination i provided by FAF data,

$\sum_{j=1}^{123} FAF_{ij}^{DE}$ is the total domestic exports from origin i provided d by FAF data,

$\sum_{j=1}^{123} FAF_{ij}^{FE}$ is the total foreign export at origin i provided by FAF data,

$FAF_{ij}^{DI\_Ton}$ is dollar-ton conversion factor for domestic import calculated by FAF data,

$FAF_{ij}^{DE\_Ton}$ is dollar-ton conversion factor for domestic export calculated by FAF data,

$FAF_{ij}^{FI\_Ton}$ is dollar-ton conversion factor foreign import calculated by FAF data,

$FAF_{ij}^{FE\_Ton}$ is dollar-ton conversion factor for foreign export calculated by FAF data, and

$VIUS_i^k$ is proportion of truck class by Vehicle Inventory Use Survey.

Fifth, after estimating freight flows between MSA regions, a doubly-constrained gravity model is applied to estimate truck O-D flows between ZIP code areas in each MSA region and between MSA regions. Doubly-constrained gravity models are appropriate when both demand and consumption are given. Although a doubly-constrained gravity model may create distortions in predicting the future due to fixed constraints of demand and consumption (Bruton 1970), the model has been successfully applied to estimate freight O-D flows in various geographies (Levine et al. 2009, Lindal et al. 2006, Prentice et al. 1998). A doubly-constrained gravity model consists of trip productions/attractions, and a travel distance friction factor (Mao and Demetsky 2002). Trip productions/attractions are obtained from the IMPLAN input-output data. Travel distance friction factors are calculated based on shortest path distances between centers of ZIP code areas which are estimated from the FAF3 network.[2]

There are two conditions to be satisfied for a doubly-constrained gravity model:
Condition 1: Sum of all trade flows from a region = that region's total supply.
Condition 2: Sum of all trade flows into a region = that region's total demand.

Values meeting these two conditions are achieved via iteration. The results are balanced trade flows.

Sixth, freight O-D flows are converted to number of trucks by applying average payload factors. FHWA provides average payload for truck classes by applying the Vehicle Inventory Use Survey. Appendix Table 1 shows the average payload for California. Truck O-D flows between ZIP code areas by truck class are estimated by dividing the gravity model results with the average payload factors. The estimated truck flows are initial truck O-D flows.

Seventh, the estimated initial O-D flows are adjusted because O-D flows estimated by commodity flows may be different from real traffic flows. Real traffic counts such as the Highway Performance Monitoring System (HPMS) at state and national levels or local survey data are often used to adjust initial O-D flows. FAF data provide Average Annual Daily Truck Traffic (AADTT), which is derived from HPMS. HPMS include traffic count data submitted by each state. So AADTT data are used to adjust the initial truck O-D flows.

AADTT is only available for 2007 or 2040, whereas the scenario of the model is for year 2030. Therefore AADTT for year 2030, which is labeled AADTT30, is calculated by interpolating between the two points. Similarly, link capacity for year 2030, which is labeled CAP30, is calculated by interpolating using 2007 and 2040 data.[3] AADTT30 includes truck flows for the nation. But this study only includes truck flows originated from California or destined to California. Therefore, the California portions are calculated from AADTT30. To do that, ton values of the projected freight flows at year 2030 are calculated from FAF O-D data. Equation (5) shows the calculation process.

$$(5)\quad CA\_Pro = \frac{\sum_{i=CA,\, j=1}^{123} Ton_{ij} + \sum_{i=1,\, j=CA}^{123} Ton_{ij}}{\sum_{i=1}^{123} \sum_{j=1}^{123} Ton_{ij}}$$

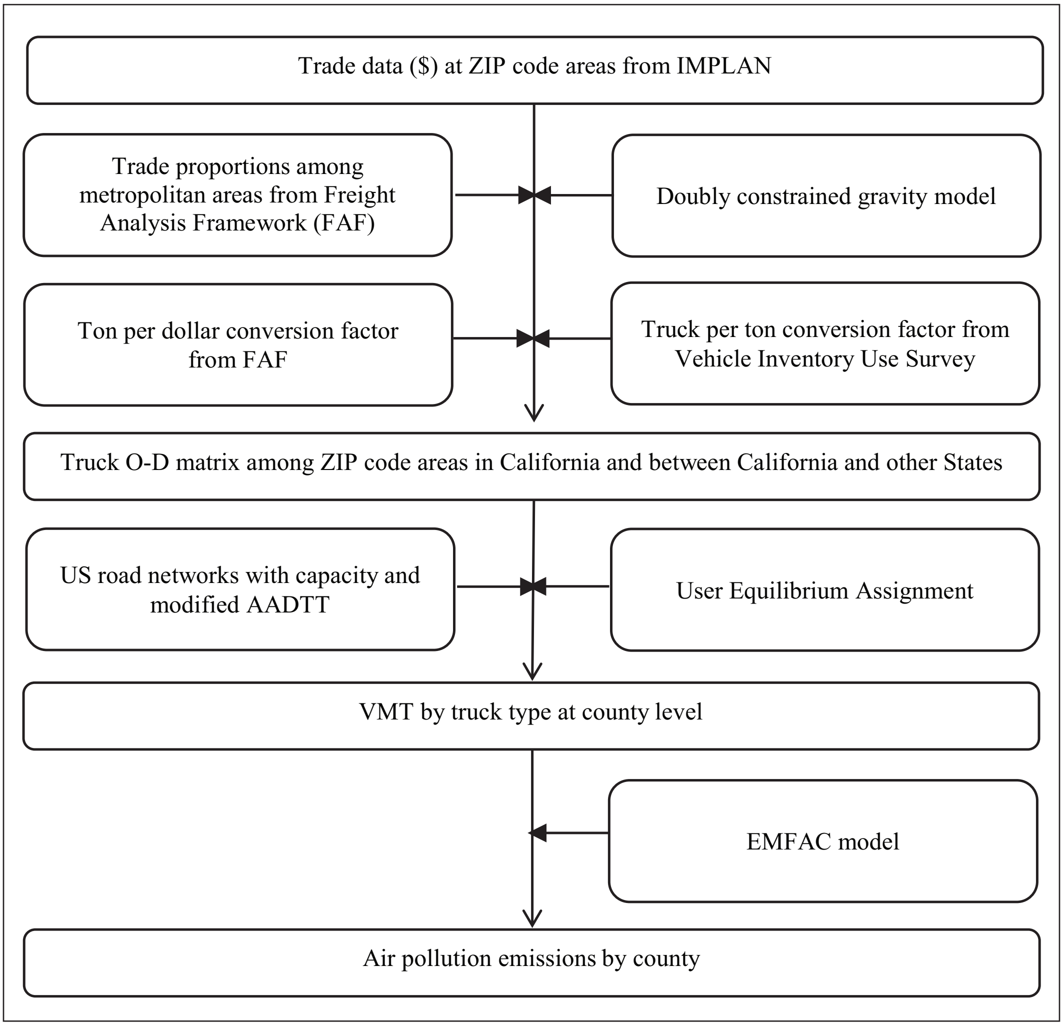
Where

CA_Pro is the proportions of freight flows originated from or destined to California out of total freight flows. i=origin, j=destination.

The calculated proportions are multiplied to the AADTT30 to estimate a modified AADTT30. The modified AADTT30 is further multiplied by VMT proportions in California MSAs to calculate AADTT30 by truck class.[4] The calculated AADTT30 by truck class is labeled tru_AADTT30. So tru_AADTT30 shows average annual daily truck traffic by truck class originated from or destined to California at 2030. To adjust the initial O-D matrix, an O-D estimation procedure developed by Nielsen (1998) and implemented in TransCAD software (Caliper 2001: page 316) is applied to tru_AADTT30 and CAP30. To convert the truck flows to passenger car equivalent (PCE), the practice from the Southern California Association of Government (SCAG) has applied which involves 1.2 for light truck, 1.5 for medium truck, and 2 for heavy truck as PCE factors. The upper portion of the Figure 1 shows the procedures for O-D estimation.

The estimated truck O-D flows are used as an input for the transportation impact model to estimate VMT on each link of the network. The User Equilibrium (UE) model, a traffic assignment model based on assumed rational behavior of humans that create equilibrium at the network level, is applied to estimate a VMT baseline and to estimate effects of various scenarios. The middle portion of the Figure 1 shows the procedures used to estimate VMT based on the estimated truck O-D flows.

Figure 1: Processes of Estimating Air Pollution Emissions



The estimated VMTs are then used as inputs for the emissions model. Air pollution emissions are estimated by applying the EMFAC model. The bottom portion of Figure 1 shows the procedures for estimating air pollution emissions based on the estimated VMT by truck class. To estimate air pollution emissions, base emission rates are first adjusted by area-specific data such as the Inspection and Maintenance (I/M) program, temperature, and relative humidity. Then total emission inventories are estimated by multiplying the adjusted emission rates by total vehicle activity. These adjustments and estimations are accomplished by applying the EMFAC model.

SCENARIOS

The model developed for this research includes a truck origin-destination (O-D) matrix at ZIP code areas for domestic and foreign trade by commodity sector. To account for the effects of interregional and international trade, the locations of a region's international gateways for trucking, such as airports, seaports, and border regions, are identified. The model includes road and highway networks that trucks utilize when traveling between O-D pairs. The model is, therefore, appropriate for identifying and analyzing changes in commodity flow patterns or changes of road network utilization and the corresponding consequences resulting in various air pollution emissions. The key idea is to implement this for various emissions control policy scenarios. Scenario results are compared to projected baseline trends.

Baseline: Future growth of foreign trade in San Pedro Bay (SPB)

This is the reference case that was used to compare and evaluate the various scenario results. The baseline shows network and emissions responses for projected growth paths. The results show the impacts on link volumes and air pollution emissions when trade via local area seaports grows in the near future. Table 4 shows projected growth at San Pedro Bay, which includes the Port of Los Angeles and the Port of Long Beach. Growth rates from 2008 to 2030, which are 170% for imports and 71% for exports, are multiplied by 2008 data for foreign trade via the port of Los Angeles and the port of Long Beach. These results show how the expected growth of trade via the ports affects commodity flows and air pollution emissions. Trade at other regions is assumed to be same as the 2008 value to isolate the effects of the growth at San Pedro Bay.

Table 4: Port of Los Angeles and Port of Long Beach Throughput Demand Forecast (Baseline)

Unit 1,000

	Actuals	Forecast	Increase	
Actual/Forecast TEU	2008	2030	TEU	%
Import Loads	7,328	19,801	12,473	170%
Export Loads	3,470	5,938	2,468	71%

Source: The Tioga Group, Inc. and IHS Global Insight. 2009.

Scenario One: Truck replacement scenario – Replacing older trucks with newer trucks. This scenario utilizes the capability of the EMFAC model, which allows users to modify the characteristics of vehicle populations including vehicle age. The Clean Truck Program (CTP) at the port of Los Angeles and the port of Long Beach has been successful in reducing truck-related emissions around the ports. According to the port of Los Angeles, CTP reduced port truck emissions by more than 80% in 2012 (Port of Los Angeles 2012). CTP was applied to drayage operations (short haul cargo container trips). For Scenario One, it is assumed that a similar program will be applied to all diesel trucks in Los Angeles County so that all diesel trucks in the county would be less than 20 years old in 2030.

Scenario Two: Network & truck improvement scenario – Developing zero emission truck lanes on I-710. Route I-710 is a major freight corridor from the port of Los Angeles and the port of Long Beach to various domestic destinations. Because communities around the freeway have been impacted by air pollution emissions, there have been various studies and plans to reduce emissions while expanding the capacity for truck flows on the freeway. Developing zero emission truck lanes is one of the plans that is relatively cost-effective and technically available. Based on the proposed plans (Metro 2012), it is assumed that four of eight lanes on I-710 will be converted to zero-emission truck lanes by 2030. It is also assumed that hybrid trucks that can be operated by electricity and by diesel engine simultaneously will be operated on the converted lanes. So 50% of the total traffic flows on I-710 will be converted to zero emissions truck flows.

Scenario Three: Land use scenario – Inland port (intermodal facility) at Mira Loma industrial area. Developing an inland port, connected by rail to the existing seaports, has been considered as a long term project to reduce truck traffic and air pollution emissions around the ports and highways. The

Mira Loma industrial area is one of the candidates for such a development (Rahimi et al. 2008). It is assumed that the inland port will begin operations in 2030. A possible development site was found from the SCAG website (Southern California Association of Government 2008: page 135, Exhibit 106). The ZIP code of the location is 91752. It is assumed that 50% of truck flows in the port of Los Angeles and the port of Long Beach are moved from the ports to the inland port for this scenario.

MODEL RESULTS

The model results at two different geographic levels, the Los Angeles MSA and Los Angeles County, are summarized. The Los Angeles MSA includes Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties. The reason that the results at two different geographies are shown is that Scenario one and three identify different implications at different geographies. A sensitivity analysis is also conducted to see how the results are sensitive to different scenarios.

Model Results for the Los Angeles MSA

Results for the Los Angeles MSA are explained in this section. Figure 2 displays a scatterplot of simulated and modified AADTT30 for the Los Angeles MSA. When the simulated and observed volumes agree 100%, the observations fall on the 45-degree line. The correlation coefficient for model results shows about 84% agreement. Table 5 shows the comparison of total volumes in the Los Angeles MSA. The difference in total volume of trucks between simulated and AADTT30 is about 900,000. In other words, total volumes of the modified AADTT30 and simulated agree over 98%. Table 6 summarizes model results of VMT for the Los Angeles MSA. To obtain VMT for the MSA, VMT by vehicle classes for each scenario are aggregated for each county within the MSA. Table 6 shows separate results for two combined counties based on results of Scenario Three. Los Angeles, Orange, and Ventura counties are combined because the three counties have a decrease in VMT for Scenario Three. Riverside and San Bernardino counties are combined because two counties show an increase in VMT for the scenario. Note that there is no change in VMT for Scenario One because of an assumption that VMT of Scenario One is the same as the one of the baseline. In Scenario Two, VMT for vehicle classes of MHDT and HHDT are reduced by 10,910 miles per day and 16,407 miles per day, respectively, due to the assumption of zero emission vehicle lanes on I-710. Total VMT reductions are 27,317 miles per day, which is a 0.07% reduction.

Figure 2: Simulated Versus Observed (Modified AADTT30) Volumes in Los Angeles MSA

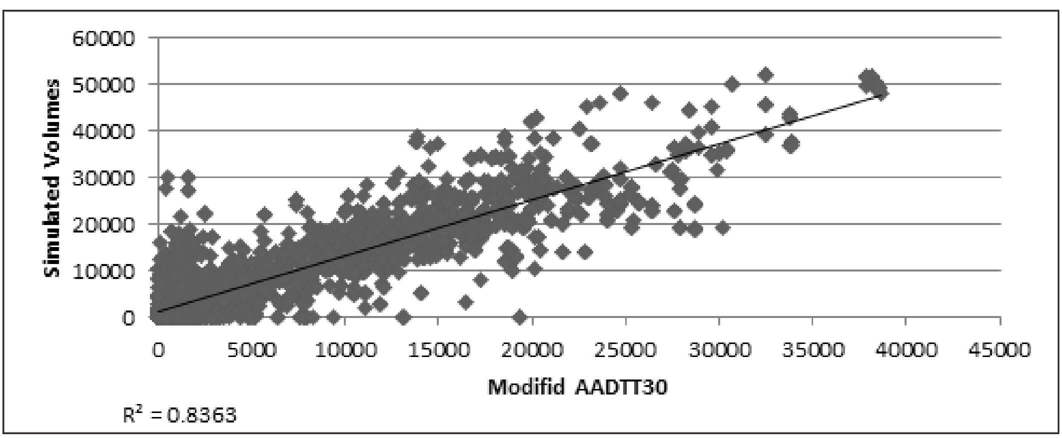


Table 5: Comparison Baseline Total Volumes in Los Angeles MSA

	Total volume of truck		Difference (Simulated-AADTT30)	
	Modified AADTT30	Simulated (Base scenario)	Number	%
Volumes	48,471,251	47,548,530	-922,721	-1.90%

Table 6: Summary of Vehicle Miles Traveled (VMT) Results, Los Angeles MSA

Units: Miles per day

Region	Vehicle class		Baseline	VMT change from scenario		
				1	2	3
Los Angeles MSA (Los Angeles + Orange + Ventura + Riverside + San Bernardino County)	LDT		23,971,075	-	-	65,143
	MDT		7,990,359	-	-	20,925
	LHDT		2,284,008	-	-	2,301
	MHDT		1,527,658	-	-10,910	2,173
	HHDT		2,308,083	-	-16,407	6,368
	Total	Number	38,081,183	-	-27,317	96,910
		%	-	-	-0.07%	0.25%
Los Angeles + Orange + Ventura County	LDT		13,501,956	-	-	-258,623
	MDT		4,500,652	-	-	-86,700
	LHDT		1,285,775	-	-	-27,309
	MHDT		859,145	-	-10,910	-17,353
	HHDT		1,287,066	-	-16,407	-24,388
	Total	Number	21,434,594	-	-27,317	-414,373
		%	-	-	-0.13%	-1.93%
Riverside + San Bernardino County	LDT		10,469,120	-	-	323,766
	MDT		3,489,707	-	-	107,625
	LHDT		998,232	-	-	29,610
	MHDT		668,513	-	-	19,526
	HHDT		1,021,016	-	-	30,756
	Total	Number	16,646,588	-	-	511,284
		%	-	-	-	3.07%

Note: LDT: Light-Duty Trucks, MDT: Medium-Duty Trucks, LHDT: Light HD Trucks, MHDT: Medium HD Trucks, HHDT: Heavy HD Trucks

Interestingly, in Scenario Three, VMT for vehicle classes are increased when 50% of the truck flows are moved from the ports of Los Angeles/Long Beach to Mira Loma area according to the model results. Total VMT increase is 96,910 miles per day, which is a 0.25% increase. That result may be because infrastructures such as freeways and distribution centers have already been developed for efficient operations around current ports. If an inland port is developed in the Mira Loma area, there would be new developments of highways, major arterials, and distribution centers to improve network accessibility of the area. Then the network model results may be different than the current results. Even though infrastructures are not fully updated to analyze the scenario, there is an important implication for policy applications from the model results.

Taking transport activities from one place to another may be helpful to reduce environmental problems for the specific area but the benefits may be offset by increased problems in other places. Therefore, analyzing the impacts of policy scenarios in various regions is useful for local area policy makers. More explanations will be developed when the Los Angeles MSA results are compared with the Los Angeles County results later in this paper.

Table 7 displays the results of air pollution emissions applying the network model results for the baseline and three scenarios of the Los Angeles MSA. Note that there are no changes for vehicle classes of LDT, MDT, and LHDT in Scenarios One and Two because the two scenarios only involve MHDT and HHDT. Scenario One shows the biggest reduction in all pollutants among all the scenarios. Notably, NOx and PM are reduced by 0.54 and 0.04 tons per day, respectively. CO2 does not change because VMT remains at the same level with the baseline. Scenario Two shows relatively small changes compared with the other scenarios. Because the change in PM is too small compared with the baseline, the results show no change. Scenario Three shows increases in three of the air pollution emissions. PM for total vehicle classes is reduced in the Los Angeles MSA, although total VMT for the region is increased as shown in Table 6. This is because PM reductions in Los Angeles, Orange, and Ventura counties are bigger than the PM increase in Riverside and San Bernardino counties.

In Scenario One, when old trucks in Los Angeles County are replaced with newer models, it will affect air pollution emissions in Los Angeles County and other counties as well. To estimate the effects in each county, truck proportions originated from Los Angeles County are estimated by using the estimated O-D matrix. Table 8 shows the calculated proportions for the Los Angeles MSA. Results for Los Angeles County, for example, show that 73% of the trucks operating in the county including both medium heavy-duty trucks (MHDT) and heavy heavy-duty trucks (HHDT), are originated within the County. In Orange County, 30% of the trucks originated from Los Angeles County. Percentages for other counties can also be interpreted in the same way.

Model Results for Los Angeles County

Table 9 shows VMT for the baseline and VMT changes for the three scenarios. For Scenario One, old trucks are replaced by newer ones but there is no change in VMT because VMT remains the same. For Scenario Two, VMT of MHDT and HHDT are reduced because 50% of truck flows for two truck classes are converted to zero emission vehicle trips on I-710. VMT for other vehicle types remain at the same level.

In Scenario Three, a relatively big decrease in VMT is shown when 50% of truck flows are moved from the ports of Los Angeles/Long Beach to the Mira Loma area. The result is also different than the one for the Los Angeles MSA. Total VMT was increased when Scenario Three was applied in the Los Angeles MSA as shown in Table 6. Part of the reason for the difference is that the Mira Loma area is located in Riverside County. Because this table only includes VMT within Los Angeles County, the result shows decreased VMT.

Table 10 displays air pollution emissions results for the baseline and the three scenarios. There are no changes for vehicle classes of LDT, MDT, and LHDT in Scenario One and Two because these two scenarios only involved MHDT and HHDT. Scenario One shows the biggest reduction in NOx and Total Organic Gases (TOG) among all scenarios. Scenario Three shows the biggest reduction in CO, CO2, and PM. Scenario Two shows the least impact in terms of reducing emissions for the county. A part of the reason for small impact of Scenario Two may be that emissions reductions in the specific area do not have much impact for the county as a whole.

Table 7: Air pollution Emissions Results for Baseline and Scenarios in the Los Angeles MSA

Units: tons per day

Baseline						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	28.73	12.09	6.67	1.35	2.98	51.82
CO	85.07	43.16	28.87	12.24	18.92	188.26
NOx	6.15	3.04	14.54	4.55	34.77	63.05
CO2 (1000)	15.84	7.32	2.17	2.41	6.12	33.86
PM	1.8	0.69	0.1	0.22	0.53	3.34
SOx	0.15	0.07	0.01	0.02	0.06	0.31
Difference from baseline						
Scenario 1						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	-	-	-	0	-0.02	-0.02
CO	-	-	-	-0.09	-0.11	-0.20
NOx	-	-	-	-0.31	-0.23	-0.54
CO2 (1000)	-	-	-	0	0	0
PM	-	-	-	-0.01	-0.03	-0.04
SOx	-	-	-	0	0	0
Scenario 2						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	-	-	-	0	0	0
CO	-	-	-	-0.02	-0.03	-0.05
NOx	-	-	-	-0.02	-0.05	-0.07
CO2 (1000)	-	-	-	-0.02	-0.03	-0.05
PM	-	-	-	0	0	0
SOx	-	-	-	0	0	0
Scenario 3						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	-0.01	0	0	0	0.01	0
CO	0.05	0.01	0.01	0.01	0.02	0.1
NOx	0.01	0.01	0.01	0	0.01	0.04
CO2 (1000)	0.02	0.02	0	0	0.01	0.05
PM	0	0	0	-0.01	-0.01	-0.02
SOx	0	0	0	0	0	0

Note: TOG: Total Organic Gases, CO: Carbon monoxide, NOx: Nitrogen oxides CO2: Carbon dioxide PM: Particulate Matter, SOx: Oxides of sulfur.

Table 8: Proportions of Trucks Originated from Los Angeles County

County	MHDT	HHDT
Los Angeles	0.73	0.73
Orange	0.30	0.30
Riverside	0.23	0.22
San Bernardino	0.22	0.21
Ventura	0.35	0.35

Source: estimated origin-destination matrix

Table 9: Vehicle Miles Traveled (VMT) in Los Angeles County

Units: Miles per day

Baseline and Scenarios		Baseline	VMT change from scenario		
			1	2	3
LDT		10,012,255	-	-	-215,567
MDT		3,337,419	-	-	-72,287
LHDT		953,527	-	-	-22,799
MHDT		637,983	-	-10,910	-14,401
HHDT		954,370	-	-16,407	-20,145
Total	Number	15,895,554	-	-27,317	-345,199
	%	-	-	-0.17%	-2.17%

Note: LDT: Light-Duty Trucks, MDT: Medium-Duty Trucks, LHDT: Light HD Trucks, MHDT: Medium HD Trucks, HHDT: Heavy HD Trucks

Sensitivity Analysis

In this section, the results from various sensitivity analyses are explained. Three different levels of implementation of each scenario are applied to examine the sensitivity of the model results.

Summary of the Sensitivity Test Results

The sensitivity test results show that the model works almost linearly for Scenarios One and Two, which means that emissions are linearly decreasing when more old trucks are replaced with new trucks in Scenario One or when more lanes are converted to zero-emission truck lanes in Scenario Two. Scenario Three shows varied results by pollutants and levels. These results would change if a different inland port site other than the Mira Loma area is selected. Overall, the model performs as expected. The sensitivity test results show different implications for each scenario.

Scenario One. TOG, CO2, PM, and SOx are not changed by replacing old trucks because truck populations, VMT, and fuel type are the same regardless of the level of implementations. CO and NOx, however, are changed although the amounts are small. The reason for small changes may be because the EMFAC model has limited capability to assess technology improvement. For example, natural gas trucks would not be included in the EMFAC model unless natural gas trucks are first produced and tested to determine emissions parameters. If alternative fuel trucks such as natural gas trucks become popular, the simulated impacts could be much bigger.

Scenario Two. Emissions for all pollutants except SOx change because VMT decreases on I-710. But the change is small because the VMT decrease on I-710 is less than 1% of the Los Angeles County total. Although truck traffic on I-710 is heavy, it is a small portion of the amount for Los Angeles County.

Scenario Three. Emissions for all pollutants except SOx are changed because VMT decreases around the ports of Los Angeles/Long Beach. But the change is small, perhaps because the VMT decrease around the ports is about 1% for all of Los Angeles County.

Important implications of the results are that infrastructure projects at a specific location would not make much impact for the whole County or MSA. Moreover, just replacing old diesel trucks with

Table 10: Air Pollution Emissions Results for Baseline and Scenarios in Los Angeles County

Units: tons per day

Baseline						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	14.02	5.67	3.14	0.7	1.04	24.57
CO	39.63	19.7	14.02	6.46	6.57	86.38
NOx	2.84	1.4	6.78	2.18	11.09	24.29
CO2 (1000)	6.94	3.18	0.95	1.02	2.37	14.46
PM	0.81	0.3	0.05	0.1	0.22	1.48
SOx	0.07	0.03	0.01	0.01	0.02	0.14
Difference from baseline						
Scenario 1						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	-	-	-	0	-0.02	-0.02
CO	-	-	-	-0.07	-0.09	-0.16
NOx	-	-	-	-0.21	-0.18	-0.39
CO2 (1000)	-	-	-	0	0	0
PM	-	-	-	-0.01	-0.01	-0.02
SOx	-	-	-	0	0	0
Scenario 2						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	-	-	-	0	0	0
CO	-	-	-	-0.02	-0.03	-0.05
NOx	-	-	-	-0.02	-0.05	-0.07
CO2 (1000)	-	-	-	-0.02	-0.03	-0.05
PM	-	-	-	0	0	0
SOx	-	-	-	0	0	0
Scenario 3						
Vehicle class	LDT	MDT	LHDT	MHDT	HHDT	Total
TOG	-0.01	0	0	0	0	-0.01
CO	-0.27	-0.12	-0.01	-0.02	-0.04	-0.46
NOx	-0.03	-0.01	-0.01	-0.03	-0.06	-0.14
CO2 (1000)	-0.12	-0.05	-0.02	-0.02	-0.04	-0.25
PM	-0.02	0	0	-0.01	-0.01	-0.04
SOx	0	0	0	0	0	0

Note: TOG: Total Organic Gases, CO: Carbon monoxide, NOx: Nitrogen oxides CO2: Carbon dioxide PM: Particulate Matter, SOx: Oxides of sulfur.

newer diesel trucks would not bring much reduction unless an innovative technology is developed. Applying cleaner fuel such as natural gas would be more promising.

Table 11 shows air pollution emissions results for three scenarios for the Los Angeles MSA. Each scenario includes three different levels, which are -25%, 0%, and 25%. Total Organic Gases (TOG) shows little change for various levels in each scenario. That is because emissions of TOG mostly depend more on vehicle population than VMT. It was assumed that numbers of vehicles are the same for all scenarios. SOx shows no changes across strategies. SOx emissions are calculated by multiplying a weight factor of sulfur in fuel by gallons of fuels consumed. Even though gallons of fuels consumed are changed by different levels of scenarios, the changes are not significant enough to make a difference so that SOx amount remains at the same level. Other pollutants show more reductions when more trucks are replaced in Scenario One or when more lanes are converted to zero-emission truck lanes in Scenario Two. Scenario Three, however, shows mixed results by pollutants and truck classes. NOx, for example, remained at the same level then decreased from

34.78 tons per day to 34.77 tons per day when more HHDT flows were moved from the port of Los Angeles/Long Beach to the Mira Loma area. CO emissions, on the contrary, increased first then decreased when more HHDT flows were relocated. The overall conclusion is that the results are not sensitive to alternative scenarios.

Table 11: Results of Sensitivity Analysis for the Los Angeles MSA

Units: tons per day

		MHDT			HHDT			Total		
		-25%	0%	25%	-25%	0%	25%	-25%	0%	25%
TOG	Scenario1	1.35	1.35	1.35	2.97	2.96	2.96	51.79	51.78	51.78
	Scenario2	1.35	1.35	1.35	2.98	2.98	2.97	51.82	51.81	51.81
	Scenario3	1.35	1.35	1.35	2.99	2.99	2.98	51.82	51.81	51.81
CO	Scenario1	12.20	12.18	12.15	18.87	18.83	18.81	188.16	188.13	188.07
	Scenario2	12.23	12.22	12.21	18.90	18.89	18.87	188.25	188.23	188.21
	Scenario3	12.24	12.25	12.25	18.92	18.94	18.92	188.29	188.35	188.34
NOx	Scenario1	4.40	4.32	4.24	34.66	34.60	34.54	62.81	62.66	62.54
	Scenario2	4.54	4.53	4.52	34.74	34.72	34.69	63.04	63.00	62.97
	Scenario3	4.55	4.55	4.55	34.78	34.78	34.77	63.07	63.08	63.09
CO2 (thousand)	Scenario1	2.41	2.41	2.41	6.12	6.12	6.12	33.83	33.83	33.83
	Scenario2	2.40	2.39	2.38	6.11	6.09	6.07	33.81	33.78	33.76
	Scenario3	2.40	2.41	2.41	6.13	6.13	6.13	33.85	33.89	33.89
PM	Scenario1	0.21	0.21	0.21	0.51	0.50	0.50	3.32	3.32	3.32
	Scenario2	0.22	0.22	0.21	0.53	0.53	0.52	3.33	3.33	3.33
	Scenario3	0.22	0.21	0.21	0.53	0.52	0.52	3.34	3.35	3.35
SOx	Scenario1	0.02	0.02	0.02	0.06	0.06	0.06	0.33	0.33	0.33
	Scenario2	0.02	0.02	0.02	0.06	0.06	0.06	0.33	0.33	0.33
	Scenario3	0.02	0.02	0.02	0.06	0.06	0.06	0.33	0.33	0.33

CONCLUSIONS AND FUTURE WORK

Estimating GHGs and other pollutants is an important basis for regional transportation planning. Treating the trucking sector has been a challenge because of data limitations. This study demonstrated how input-output data at the ZIP code level along with Freight Analysis Framework (FAF) data can be applied to estimate truck flows between sub-state areas and how the estimated truck flows can be used to evaluate various policy scenarios involving reduced air pollution emissions.

The model developed here was used to evaluate three plausible policy alternatives: 1) How much air pollution emissions such as PM and NOx are reduced by replacing old trucks with newer models in Los Angeles County and how great are the impacts throughout the Los Angeles MSA due to a truck upgrade in Los Angeles County. 2) How much air pollution emissions are reduced by introducing zero emission lanes on I-710 in Los Angeles County, 3) How much air pollution emissions are reduced by developing an inland port at the Mira Loma area for Los Angeles County as well as throughout the Los Angeles MSA.

It was found that a truck replacement strategy can be effective for reducing air pollution emissions in both Los Angeles County and the surrounding MSA. Introducing zero emission lanes on a major truck highway can deliver small impacts in the county or surrounding MSA region, although it may have a significant impact to reduce air pollution emissions in specific local areas.[5]

Developing an inland port, however, can increase air pollution emissions in the MSA, although it can reduce emissions around the port area.

By analyzing and comparing the results of three scenarios, various lessons were learned. First, when a policy alternative is considered to reduce air pollution emissions, it is important to make the objectives clear. There can be a strategy that reduces air pollution emissions in a specific area but increases emissions in the surrounding county or MSA. Similarly there can be a strategy that reduces air pollution emissions in the county or MSA, although the reduction in a specific area is not likely. If the objective is to reduce overall air pollution emissions in large areas, the vehicle replacement strategy seems to be promising. If the objective is to reduce air pollution emissions in a specific area such as near highway segments, developing zero emission truck lanes could be a good option. Second, moving transport activities from one site to another could have both positive and negative impacts. Total air pollution emissions may not be changed, although emissions in a local area could be reduced. There are also possibilities to increase overall emissions if proper developments of infrastructure are not implemented. More studies are needed to more thoroughly evaluate land use change.

The model developed here has limitations. First, the model may not evaluate congestion effects properly because only freight flows were included and passenger car flows are not yet added in the assignment. When both passenger car flows and truck flows are added, the results can be different. Second, new technologies can change the model results. For the truck replacement scenario, it was assumed that old diesel trucks are replaced with newer diesel trucks. Recently however, significant natural gas reserves have been developed in the U.S. It is possible that natural gas trucks will be more popular in 2030 because natural gas is likely to be cheaper than diesel. Of course there must be investments in developing efficient trucks, and proper infrastructures must be established to make natural gas trucks popular. Natural gas trucks could not be included in truck replacement strategy because the EMFAC model does not yet include that fuel category. If natural gas trucks are included in the model, there could be more reductions in air pollution emissions. Third, changes in supply chains, such as those prompted by the Panama Canal expansion or opening of the Northern Sea Route, also known as the Northeast Passage, can affect model results. The baseline origin-destination truck flows matrix does not take into account the Panama Canal expansion or opening of the Northern Sea Route. If significant changes in supply chains are assumed due to the opening of the two new routes, freight flows in the Port of Los Angeles and the Port of Long Beach can be changed affecting truck flows and the corresponding air pollution emissions. It is not yet known the extent to which the changes would be a paradigm shift or if most current trends would be continued.

The limitations of the developed model suggest the next steps for the research. Because including passenger vehicles is important for estimating congestion effects, both passenger trips and freight trips need to be combined in the model. The model can also be updated when more fuel types such as natural gas are modeled in the EMFAC model. The model developed here has a capability to test scenarios involving VMT changes at the sub-county levels. The current state of the EMFAC model, however, does not permit us to go to that next step. If and when EMFAC is suitably updated to treat smaller areas, our model will become more useful.

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Endnotes

1. All other MSAs and remainders are labeled as Other States for illustration purposes. Other States includes 118 FAF regions except California.

2. Shortest path distance is used as a friction factor, although travel time may be more realistic. This was the choice because passenger flows were not yet included in the study. Travel time will be used in future work when all vehicle flows are included in the model.

3. AADTT30=AADTT07+((AADTT40-AADTT07)/33)*23. Similarly CAP30=CAP07+((CAP40-CAP07)/33)*23.

4. The EMFAC model requires VMT by truck class to estimate emissions. Therefore, VMT has to be estimated by truck class. To be consistent with the EMFAC model, VMT by truck is obtained from EMFAC and the proportions are calculated. The calculated proportions are as follows: Light Duty Truck (LDT) = 0.63 (LDT1=0.15, LDT2=0.48), Medium Duty Truck (MDT) = 0.21, Light Heavy Duty Truck (LHDT) = 0.06 (LHDT1=0.05, LHDT2=0.01), Medium Heavy Duty Truck (MHDT) = 0.04, Heavy Heavy Duty Truck (HHDT) = 0.06.

5. The EMFAC model that was applied for estimating air pollution emissions is for county-level estimations; emissions are estimated only at the county level. In Scenario Two, unlike the other two scenarios, emissions reductions occur only on the I-710 link, which is in the scenario area. If only the surrounding area of I-710 is selected, the impact of Scenario Two can be significant. The argument becomes clearer when the % changes of Scenario Two are compared. In Los Angeles County, for example, CO reduction in percentage terms was 0.03%, but 0.06% in the Los Angeles MSA. Estimating impacts in smaller areas below the county level will be a next step of this research.

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Appendix Table1: Bridge of Vehicle Class Categories Between VIUS and EMFAC

VIUS			EMFAC			Adjusted Avg. payload (lbs)
Vehicle group	Gross Vehicle Weight	Avg. Payload(lbs) for California	Vehicle class	Description	Weight Class(lbs)	
Group 1	Less than 6,000 lbs.	-	LDT1	Light-Duty Trucks	0-3750	2,116
			LDT2	Light-Duty Trucks	3751-5750	
Group 2	6,001 to 10,000 lbs.	2,116	MDT	Medium-Duty Trucks	5751-8500	
			LHDT1	Light-Heavy-Duty Trucks	8501-10000	
Group 3	10,001 to 14,000 lbs.	3,945	LHDT2	Light-Heavy-Duty Trucks	10001-14000	3,945
Group 4	14,001 to 16,000 lbs.	4,560	MHDT	Medium-Heavy-Duty Trucks	14001-33000	11,797
Group 5	16,001 to 19,500 lbs.	5,097				
Group 6	19,501 to 26,000 lbs.	8,518				
Group 7	26,001 to 33,000 lbs.	29,012				
Group 8	More than 33,000 lbs	31,550	HHDT	Heavy-Heavy-Duty Trucks	33001-60000	31,550

Data: Vehicle Inventory Use Survey 2002 (http://ops.fhwa.dot.gov/freight/freight_analysis/faf/faf2_reports/reports9/s501_2_3_tables.htm#_Toc169399555), EMFAC model
Note: Group 1 of VIUS has too little sample to calculate average payload
Same payload is applied for LDT1, LDT2, MDT, and LHDT1

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Factors Contributing to School Bus Crashes

by Shamsunnahar Yasmin, Sabreena Anowar, and Richard Tay

School bus safety is a community concern because parents expect their children to be transported to and from school safely. However, relatively few studies have been devoted to examining the factors contributing to school bus crashes. In this study, a logistic regression model is used to delineate the factors that contribute to school bus collisions from collisions involving other types of buses. As expected, we find significant differences in crash factors arising from differences in exposure and operating characteristics. Surprisingly, we also find that school bus drivers are more likely to commit driving violations or errors than non-school bus drivers.

INTRODUCTION

Road safety is a serious issue around the world, with more than 1.2 million people killed every year (WHO 2004). In the Province of Alberta in Canada alone, nearly 400 people are killed and more than 27,000 people are injured in over 112,000 motor vehicle collisions each year (AT 2006). The direct social cost of motor vehicle collisions to Albertans is as much as $4.68 billion, or 2.4% of Alberta's gross domestic product. Although school buses (SB) were involved in only 0.4% of the total number of collisions occurring in Alberta in the last decade, these crashes tend to receive disproportionate attention in the media and the community because of the high safety expectations for SB and the intensity of emotions involved when school children are injured.

SB safety has a high priority in the community because parents put their trust in schools and SB drivers to transport their children to and from school safely. About 6,000 SBs in Alberta, Canada, travel over 76 million kilometres each year to transport approximately 126,000 students in rural areas and 139,000 students in urban areas (Opus Hamilton 2008) and they are considered to be one of the safest modes. The proportion of SB collisions resulting in injury is 13.7%, while the share of total collisions in Alberta that results in injury during the same time period is 15.2% (Opus Hamilton 2008). Thus, there is a slightly lower risk of SB collisions resulting in injuries compared to all collisions.

Nevertheless, SB accidents do occur and sometimes with tragic consequences. They also tend to be followed by public demand for actions that may not be supported by theory or evidence. Hence, any collision involving an SB is a cause for concern, especially when it results in casualties among our most vulnerable population. To ensure even greater safety of SB operation, it is necessary to identify the factors that are responsible for SB-related accidents in order to provide evidence-based recommendations to improve the safety performance of these buses.

The objective of this research is to identify the factors associated with SB crashes that significantly differ from the factors associated with other bus crashes in Alberta. Since very few previous studies pertaining to SB-related collisions are found, this research aims to provide valuable insight to transportation and safety professionals in identifying safety issues and assist them in making decisions that will enhance SB safety. To achieve this objective, this paper first reviews the relevant literature and develops a simple conceptual framework to identify some potential factors contributing to SB crashes that may be different from those contributing to crashes involving other types of bus collisions. To test the hypotheses, descriptive analyses and Chi-square tests of the characteristics of SB and non-SB collisions are performed using data from the Canadian province of Alberta. In addition, a logistic regression model of SB and non-SB crashes is estimated.

LITERATURE REVIEW

Despite being a considerable community concern, the literature survey did not find many studies on the statistical analysis of factors contributing to SB collisions. Most studies analyze collisions involving all types of buses and coaches but do not separate SBs from other buses, with a few studies investigating only transit buses or coaches (Albertsson and Falkmer 2005, Rahman et al. 2011, Evans and Courtney 1985, Barua and Tay 2010, Chimba et al. 2010, Zegeer et al. 1994, Tseng 2012, Mohamed et al. 2012). In one of the few studies that examine SB crashes, Yang et al. (2009) applied Chi-square tests to determine the differences in crash and injury characteristics between SBs and other vehicles in the state of Iowa. They found that day of week, time of day, speed limit, driver characteristics, and vehicle characteristics are significant factors associated with SB crashes and injuries, and that drivers of other vehicles are more likely to have caused SB crashes.

Besides these works, few published studies examine the prevalence of SB crashes and most analyze the biomechanics of SB occupant injuries and fatalities. For examples, Hinch et al. (2002) focus on design features inside SBs while McGeehan et al. (2006) use data from medical sources to identify different types of injury. They found that motor vehicle collisions account for 42.3% of SB-related injuries, followed by injuries sustained while boarding or alighting the bus (23.8%). Lapner et al. (2003) examine frontal collisions and rollover crashes, which are most likely to result in fatality or severe injuries, and found that they are relatively rare and contribute mainly to head, neck, and spine injuries. Some studies examine the annual cost of SB-related crashes. For example, Miller and Spicer (1998) found that SB injuries account for half of all school injury deaths in the United States and estimate the annual social cost of SB related collisions as $330 million.

CONCEPTUAL FRAMEWORK AND RESEARCH HYPOTHESES

There are several reasons why the characteristics of vehicle collisions involving buses should be different between SB and non-SB crashes. The most obvious is the difference in exposure, which has a direct influence on crash risks. Extant research finds that day-of-week and time-of-day have a significant impact on many types of vehicle crashes (Kim et al. 2008, Chen et al. 2012, Anowar et al. 2013). Unlike other types of buses (transit bus, tour coach, and private bus), SBs operate mostly during the beginning and ending of a school day. Thus, relative to non-SBs, SBs are hypothesized as being more likely to crash during weekdays relative to weekends. They are also hypothesized to be more likely to crash during morning and afternoon peak periods relative to night-time and off-peak periods. Moreover, since many schools are closed for extended periods during the summer calendar months, SBs are also hypothesized as being less likely to crash during summer (season of the year).

Besides the four seasons, weather and road surface conditions are other seasonal factors that affect vehicle crashes (Kim et al. 2007, Lee and Abdel-Aty 2005, Anowar et al. 2013). Although weather and road surface conditions are expected to be correlated, they do measure some distinctive effects. First, roads are more likely to be covered in snow during winter even though it may not be snowing on a particular day, especially for local roads where the SBs tend to ply. Second, bad weather affects visibility and sight distances more while a wet or snowy road surface condition affects mostly traction, steering, and control. In terms of visibility, however, SBs may be more visible in bad weather than non-SBs because of their bright yellow color, stop signs, and flashing lights. Consequently, relative to non-SBs, SBs are hypothesized as being more likely to crash on roads covered with snow (road surface condition) but less likely to crash during snowy weather (weather condition).

Another environmental factor that has been found to be significant in road safety is location. In this regard, there are some major differences in the locations where SBs operate compared with non-SBs. For example, unlike transit buses, which mostly operate in urban areas, SBs have a significant presence in rural areas. Past research has found that a higher proportion of rural students use SBs than their urban counterparts because travel choices are limited in rural areas (Tucker 2008). Furthermore, the distances travelled by school children are longer in the rural areas (Kmet and Macarthur 2006). Hence, relative to non-SBs, SB crashes are hypothesized to occur more in rural areas than urban areas.

SBs are also operated differently because of differences in their trip demands or usage, which may result in different types of crashes. The types of crashes have been found to be a significant factor in traffic safety (Abdel-Aty 2003, Haleem and Abdel-Aty 2010, Obeng 2007, 2011). For example, relative to non-SBs and especially non transit buses, SBs involve more frequent stops and starts to pick up or drop off school children. These stop and start operations increase the likelihood of rear-end collisions. Moreover, drivers are not supposed to overtake an SB that has stopped to pick up or drop off students. Therefore, relative to non-SBs, SBs are hypothesized as more likely to be involved in rear-end collisions than passing and sideswiping crashes. They are also hypothesized to be more likely to experience impact at the rear but less likely to experience impact at the front or side. Moreover, SBs are generally driven at lower speeds relative to non-SBs (e.g., non-transit buses like tour buses and private buses) and this contributes to their lower crash severity. Thus, relative to non-SBs, SBs are hypothesized to result in crashes of lower severities. Additionally, they are less likely to be involved in rear-end crashes, which usually involve single or multiple vehicles, but as posited above, they are more likely to be involved in rear-end crashes, which usually involve two vehicles. More importantly, they are less likely to speed and be involved in single vehicle run-off-road crashes. Also, because of their visibility and the tendency of drivers to slow down when approaching a stopped SB, they are less likely to be involved in crashes involving more than two vehicles. Hence, relative to non-SBs, SBs are hypothesized as being more likely to be involved in two-vehicle collisions than single or multiple vehicle collisions.

Besides the types of crashes, the types of roadways have been found to be an important determinant in traffic safety (Abdel-Aty and Keller 2005, Abdel-Aty and Haleem 2011, Haleem et al. 2010, Rifaat et al. 2012a). Since SBs tend to operate more often on local roads than non-SBs, they are hypothesized as more likely to crash at intersections without traffic signals. Also, vehicle characteristics are important factors in road safety (Obeng 2011, Tay et al. 2009, 2010, Barua et al. 2010, Tay 2003, 2002). And driver characteristics have been widely found to be a significant contributing factor (Obeng 2007, Wang and Abdel-Aty 2008, Anowar et al. 2013). SBs are more likely to be operated by female drivers compared with non-SBs. For example, according to one employment agency, 60% of SB drivers in 2011 in Canada were females while only 15% of non-SB drivers were females.[1] The dominance of female drivers is confirmed by Parkland School Division (approximately 60%) and Black Gold Regional Schools (71.2%).[2] Additionally, SBs are also more likely to be operated by older drivers (65 and above), and older drivers have been found to have higher crash risks (Tay 2012, 2008, 2006). Therefore, relative to collisions involving non-SBs, those involving SBs are hypothesized as more likely to involve a female driver and/or an older driver.

Finally, aberrant behaviors defined as driver errors and violations are widely considered to be major causes of road crashes (Rifaat et al. 2012b, Yasmin et al. 2012). Following, Reason et al. (1990) and Parker et al. (1995), driving errors are defined as the failure of planned actions to achieve their intended consequences (e.g., underestimating speed of oncoming vehicles when overtaking) and driving violations are defined as deliberate deviations (e.g., speeding) from those practices believed necessary to maintain the safe operation of a potentially hazardous system. Since safety is one of the major considerations in the selection of SB drivers, they are expected to be less likely to be assessed as having committed traffic violations and errors in the event of a crash. And there are many training programs available for SB drivers to improve their driving, some of which are subsidized by the government. Hence, relative to collisions involving non-SBs, drivers in collisions involving SBs are hypothesized as being less likely to be assessed as having committed a driving violation or error.

Of note, however, is that the factors contributing to any road traffic collision are numerous and often interrelated. The analytical framework developed thus represents only a partial view of these complex relationships, and the factors chosen are based primarily on data available in police collision reports. Nevertheless, it presents a reasonably strong case for the need to examine the different factors contributing to SB and non-SB collisions but does not determine the likelihood or frequency of a SB crash occurring. Although exposure variables are critical in crash likelihood or crash frequency models, they are not important in differentiating whether a bus that has already crashed is more likely to be an SB or another type of bus. However, it is reasonable to assume that traffic volume will have similar effects on SB and non-SB with respect to where the crash occurs, what time the crash occurs, what type of road the crash occurs on, and the weather and road surface conditions.

METHODS

Data

Data for this study are extracted from the official crash database provided by Alberta Transportation. The database consists of all police reported crashes in the province from 1999 to 2008. The severity of a crash is determined by the person with the most severe injury and a crash is considered fatal if at least one person dies within 30 days of the collision. Also, a crash is considered injurious if at least one person suffered injuries, and a property damage only crash is that in which no injury occurred but damage of at least $1,000 was sustained. The crash records contain common types of information on collisions including the time, location, and severity of collisions as well as data on the driver, crash types, vehicle, environment, and any special road features at crash locations.

Since the focus of this study is to identify the factors differentiating SB crashes from other bus crashes in Alberta, all crashes involving at least one bus are extracted for analysis. SBs include both the traditional yellow SBs and transit SBs, because some of the SB routes, especially for high schools, are operated by public transit agencies such as Calgary Transit. The comparison group include inter-city buses, non-school route transit buses, tour buses, and other special buses. The final sample consists of 8,576 bus-related collisions for the ten-year period (1999-2008), and of these, 38.1% are SB collisions and 61.9% are collisions involving non-SBs.

Preliminary Analyses and Chi-Square Tests

Based on the information available in the dataset, 20 factors are selected for analysis. Broadly, these factors are categorized into crash characteristics, vehicle characteristics, environmental conditions, traffic control, operational characteristics, and driver characteristics. Preliminary analysis excluded statistically insignificant factors resulting in the 14 factors in Table 1. The distributions of collision characteristics of SB and non-SB collisions are reported in Table 1, which also shows the Chi-square tests used to identify those factors that differ significantly between the two types of collisions.

Table 1: Distribution of Crash Characteristics (%)

Variables	School Buses	Other Buses	χ^2- Stat
Crash Severity			
Casualty (Fatal or Injury)	18.64	19.86	1.66
Property Damage Only	81.36	80.14	
Season***			
Winter	60.04	50.39	166.99
Spring	14.46	13.96	
Summer	9.16	20.37	
Autumn	16.34	15.28	
Day of Week ***			
Weekend	3.21	16.57	303.41
Weekdays	96.79	83.43	
Time of Day***			
6.00 a.m. - 8.59 a.m.	37.61	18.33	654.49
9.00 a.m. - 2.59 p.m.	28.27	32.82	
3.00 p.m. - 5.59 p.m.	30.98	28.00	
6.00 p.m. - 6.00 a.m.	3.14	20.84	
Region ***			
Rural	12.62	4.23	180.79
Urban	87.38	95.77	
No. of Vehicles Involved***			
Single	5.55	5.82	15.78
Two	88.93	86.28	
Three or more	5.52	7.90	
Primary Event***			
Struck Object	10.31	11.83	205.32
Off-road	2.24	0.89	
Passing	2.42	6.90	
Angular	23.62	24.98	
Sideswipe	18.61	23.28	
Rear-end	31.95	24.77	
Head-on	2.02	1.21	
Backing	7.10	3.51	
Other	1.73	2.61	
Weather Condition***			
Clear	80.60	79.03	21.32
Rain	3.03	4.70	
Hail/sleet	0.47	0.59	
Snow	13.20	13.94	
Other	2.70	1.74	

(Table 1 continued on p. 68)

Table 1: Distribution of Crash Characteristics (%) cont.

Variables	School Buses	Other Buses	χ^2- Stat
Road Surface***			
Dry	49.73	56.96	85.74
Wet	7.86	10.96	
Snowy	41.04	31.04	
Other	1.37	1.04	
Driver Gender ***			
Female	59.43	19.61	1226.67
Male	40.57	80.39	
Driver Age***			
Age less than 25	3.17	2.46	116.94
Age 25 to 44	46.52	40.60	
Age 45 to 64	43.89	54.30	
Age 65 and above	6.42	2.63	
Driver Action***			
Driving Properly	55.68	67.92	120.67
Driving Violation	17.67	11.15	
Driving Error	19.62	15.36	
Other Driver Action	7.03	5.57	
Point of Impact***			
Right Front	8.04	10.30	133.22
Right Center	5.48	9.73	
Right Rear	11.07	10.56	
Back Center	26.29	18.63	
Left Rear	5.63	8.41	
Left Center	6.02	6.35	
Left Front	9.34	11.64	
Front Center	26.61	23.18	
Other Point of Impact	1.51	1.19	
Traffic Control***			
Uncontrolled	58.24	59.02	169.12
Traffic Signal	22.47	31.15	
Stop Sign	10.64	5.40	
Yield Sign	4.69	1.95	
Other	3.97	2.49	
Note: *, ** & *** denote statistically significant differences at α=10, 5 & 1%, respectively			

Logistic Regression Model

Since collision characteristics tend to be multivariate and interrelated, a multivariate analysis is conducted. The dependent variable in this analysis (SB or other bus crash) is a dichotomous outcome which facilitates the application of a binary logit or probit model. The main difference between the logit and probit models lies in the assumption regarding the distributional form of the error term. The logit model assumes a logistic distribution, whereas the probit model assumes a normal distribution. In practice, however, many studies have found that the results from both models are similar (Maddala 1983, Kennedy 2001, Greene 2003). The binary logistic model is chosen in this study because it is more commonly used than the probit model (Kennedy 2001). With this choice, the conditional probability π of a positive outcome (SB) is determined in the following equations:

(1) $$\pi(\mathrm{x}) = \frac{\exp(g(\mathrm{x}))}{1+\exp(g(\mathrm{x}))}$$

(2) $$\ln\left[\frac{\pi(\mathrm{x})}{1-\pi(\mathrm{x})}\right] = \beta \mathrm{X}$$

where X is a vector of contributing factors and β is a vector of coefficients to be estimated. The likelihood function is given by:

(3) $$l(\beta) = \Pi_{i=1}^{n} \pi(\mathrm{x}_i)^{y_i} \; (1 - \pi(\mathrm{x}_i)^{1-y_i}$$

where n is the number of observations and denotes the i^{th} observed outcome, with the value of one for an SB crash and zero for a crash involving other types of buses (non-SB). The best estimate of β is obtained by maximizing the log likelihood function:

(4) $$\mathrm{LL}(\beta) = \sum_{i=1}^{n} \{y_i \ln(\pi(\mathrm{x}_i)) + (1-y_i)\ln(1-\pi(\mathrm{x}_i))\}$$

The statistics software, Stata version 12, is used for the model estimation and hypothesis testing.

Since all contributing factors (e.g., day-of-week) are categorical, several dummy variables (e.g., weekdays and weekends) are defined for each, and one variable (e.g., weekdays) is used as the reference in the estimation. From the calibrated model, the effects of these identified factors on bus collisions are examined by comparing the β values of the dummy variables against the reference case (no coefficient estimated). If the estimated β_i is greater than zero it indicates the probability that a crash involving SB increases when a variable X_i changes from zero to one and vice-versa. In addition it is customary to calculate the odds ratios in a binary logistic model. The odds ratio (OR_i) of a variable X_i is equal to $\exp(b_i)$ and ranges from zero to positive infinity. This ratio indicates the relative amount by which the odds of an outcome (SB crash) increases ($OR_i > 1$) or decreases ($OR_i < 1$) when the value of a corresponding independent variable (X_i) increases by one unit or changes from zero to one.

Some of the coefficients of the variables within a factor were not statistically significant but are retained in the final model specification. This is done when at least one of the variables is statistically significant. Kockelman and Kweon (2002) suggest that variables with low statistical significance may be retained in the model if they belong to factors that have some significant effects on model outcome. Though this approach reduces the efficiency of the estimates, it is adopted for ease of comparison and interpretation of the estimates. This potential decrease in efficiency is compensated by using a more liberal confidence level of 90% instead of the traditional 95% (Tay et al. 2008, 2009, 2011).

RESULTS AND DISCUSSIONS

The descriptions and distributions of the significant variables are shown in Table 1. The differences in the distributions of all the contributing factors are found to be statistically significant using the Chi-square test. Moreover, the distributions of most of the contributing factors are consistent with the hypotheses except driver action. These results provide some support for our analytical framework and research hypotheses. The results of the binary logit model are reported in Table 2. Overall, they show that the model fits the data very well with a very large Chi-square statistic, very small p-value, and reasonably large pseudo R-Square. Again, a positive coefficient of a variable in the table indicates over-representation in SB crashes and a negative coefficient indicates under-representation in SB crashes in comparison with non-SB crashes. Clearly, the results support most of the hypothesized relationships about differences in the factors contributing to SB-involved collisions and non-SB-involved collisions except driver action.

In Table 2, the estimated coefficient and odds ratio ($\beta = -0.221$; OR = 0.802; $p = 0.005$) shows that casualty is less prevalent in SB-involved crashes than non-SB crashes, a finding that is consistent with Yang et al. (2009). This might be the result of improvements implemented in the school transportation sector of Alberta, including SB driver training programs, SB design, and the introduction of several safety devices on SBs (for example: reflective tapes, red flashing lights, strobe lights, and stop arms). The lower driving speed of SBs also contributes to the lower likelihood of a casualty collision.

The estimated odds ratio of seasonal distributions of these crashes suggests that SB crashes are less likely to occur during the summer (OR = 0.434; $p < 0.001$) than other seasons. This result is consistent with Yang et al. (2009) and can be attributed to the fact that most schools in Alberta normally close for vacation during the summer, resulting in lower exposure of SBs to crashes. Also consistent with Yang et al. (2009) is the finding in this study that SB crashes are less likely to occur during weekends (OR = 0.229; $p < 0.001$) compared with non-SB crashes. Again, this finding may simply be due to the fact that most schools are closed on weekends, thereby reducing the exposures of SBs to crashes. This exposure reduction will result in under-representation of SBs in crashes compared with non-SBs.

As expected (Yang et al. 2009), this study finds that SB collisions are more likely to occur during the morning (OR = 2.072; $p < 0.001$) and afternoon (OR = 1.162; $p = 0.041$) peak periods. These periods are times of highest activities for SBs: picking-up and dropping-off of students before and after school. And the close overlaps of the school start time with the general morning peak period and the school end time with the afternoon peak period increase the likelihood of an SB being involved in a crash during peak periods. The model estimates also show that SB crashes are more likely to occur in rural areas compared with non-SB crashes (OR = 3.937; $p < 0.001$). Past research identifies some differences between urban and rural school transportation operation, with a higher proportion of rural students using SB than their urban counterparts because travel choices are limited in rural areas (Tucker and Pollett 2008) and travel distances longer (Kmet and MacArthur 2006). Thus, the greater exposure on rural roads might lead to over-representation of crashes involving SBs in rural areas compared with urban areas.

Another result in Table 2 is that multiple vehicle SB collisions are less prevalent (OR = 0.706; $p = 0.003$) than single- or two-vehicle SB collisions. Drivers in Alberta are legally required to drive more cautiously (or come to a complete stop) when approaching or passing an SB, and the bright yellow color of SBs help drivers see these vehicles from a distance, which in turn reduces the probability of multiple-vehicle collisions. From the parameter estimate ($\beta = 0.464$; $p < 0.002$), it is inferred that a crash involving an SB driver backing or reversing is more likely to occur (OR = 1.591) compared with a rear-end or angular collision. This finding is consistent with Yang et al. (2009). Backing-up manoeuvres for SBs are also identified by Alberta Transportation (Opus Hamilton 2008) as high-risk activities. Poor lines of sight when backing might explain this risk.

Table 2: Estimation Results

Number of Observation	7480			
Log-likelihood at Convergence	-3567.846			
Log-likelihood at Zero	-4931.854			
Chi-Square	2728.016			
Pseudo R-square	0.277			
Variables	**Coefficient**	**Std. Err.**	**P-value**	**Odds Ratio**
Crash Severity (Base: Property Damage Only)				
Casualty	-0.221	0.079	0.005	0.802
Season (Base: Winter, Spring, Autumn)				
Summer	-0.836	0.093	< 0.001	0.434
Day of Week (Base: Weekdays)				
Weekend	-1.476	0.128	< 0.001	0.229
Time of Day (Base: 9.00 a.m. - 2.59 p.m.)				
6.00 a.m. - 8.59 a. m	0.729	0.075	< 0.001	2.072
3.00 p.m. - 5.59 p.m.	0.150	0.073	0.041	1.162
6.00 p.m. - 6.00 a.m.	-1.627	0.132	< 0.001	0.196
Region (Base: Urban)				
Rural	1.370	0.124	< 0.001	3.937
No. of Vehicles Involved (Base: Single, Two)				
Three or more	-0.348	0.119	0.003	0.706
Primary Event (Base: Rear-end, angular)				
Struck Object	-0.172	0.103	0.096	0.842
Off-road	0.461	0.290	0.112	1.586
Passing	-0.763	0.164	< 0.001	0.466
Sideswipe	-0.185	0.085	0.029	0.831
Backing	0.464	0.147	0.002	1.591
Head-on	0.321	0.241	0.182	1.379
Other	-0.332	0.213	0.119	0.717
Weather Condition (Base: Clear, Rain)				
Hail/sleet	-0.676	0.402	0.093	0.509
Snow	-0.462	0.096	< 0.001	0.630
Road Surface (Base: Dry)				
Wet	-0.209	0.106	0.048	0.811
Snowy	0.176	0.075	0.018	1.193
Driver Gender (Base: Male)				
Female	1.748	0.062	< 0.001	5.746
Driver Age (Base: Age 25 to 44)				
Age less than 25	0.346	0.180	0.054	1.413
Age 45 to 64	-0.134	0.063	0.032	0.874
Age 65 and above	1.272	0.145	< 0.001	3.568

(Table 2 continued on p. 72)

Table 2: Estimation Results cont.

Variables	Coefficient	Std. Err.	P-value	Odds Ratio
Driver Action (Base: Driving Properly)				
Driving Violation	0.616	0.093	< 0.001	1.852
Driving Error	0.606	0.087	< 0.001	1.833
Other Driver Action	0.715	0.123	< 0.001	2.045
Point of Impact (Base: Right Rear, Left Center, Left Front, Front Center)				
Right Front	-0.122	0.106	0.249	0.885
Right Center	-0.462	0.120	< 0.001	0.630
Back Center	0.332	0.081	< 0.001	1.394
Left Rear	-0.366	0.122	0.003	0.694
Other Point of Impact	-0.374	0.285	0.189	0.688
Traffic Control (Base: Uncontrolled)				
Traffic Signal	-0.142	0.072	0.050	0.868
Stop Sign	0.488	0.114	< 0.001	1.628
Yield Sign	0.719	0.176	< 0.001	2.052
Other Traffic Control	0.294	0.167	0.078	1.342
Constant	-1.276	0.104	< 0.001	–

Among other primary events, striking an object (OR = 0.842; p = 0.096), passing (OR = 0.466; p < 0.001), and sideswipe (0.831; p = 0.029) are under-represented in SB-related collisions.

SB crashes are also found to be weakly related to hail and sleet (OR = 0.509; p = 0.093) and strongly related to snow (OR = 0.630; p < 0.001). This could be because SB drivers travel at slower speeds, maintain longer headways, and use more caution while driving in these adverse weather conditions. Again, the bright yellow color of the SB improves visibility in poor weather, thereby reducing the likelihood of these buses being involved in crashes. Further, its parameter estimate of 0.176 suggests that SB crashes are over-represented on road surfaces with snow (OR = 1.193), implying that SBs are more susceptible to collisions on such roads than non-SBs. This may be explained by the fact that SBs operate more than non-SBs on local roads where snow is not removed and the roads are not de-iced as often as main roads. This result also shows that SB collisions are under-represented on wet road surfaces (OR = 0.811; p = 0048), which can be explained by the fact that most SB drivers drive cautiously by maintaining longer headways and driving at lower speeds on wet road surfaces (Shankar and Mannering 1996).

On the issue of gender, this study finds that female SB drivers are involved in collisions more than male SB drivers compared with non-SB drivers (OR = 5.746; p < 0.001). As discussed earlier, females comprise approximately 60% of SB drivers in Alberta, and this increased exposure might explain their over-representation in crashes. This result may also be explained by the perceived behavior and driving skills of female drivers. Due to the size of an SB and the frequent on-street stops it makes, rear-end and sideswipe crashes are the most common SB crashes (Opus Hamilton 2008). In addition, compared with male drivers, female drivers have slower reaction times (Mehmood and Easa 2009) and are more prone to distractions, making perceptual and judgmental errors and lapses (Reason et al. 1990), which might also contribute to the higher likelihood of female SB drivers' involvement in collisions.

SB crashes involving young drivers aged less than 25 (OR = 1.413; p = 0.054) and older drivers aged 65 and above (OR = 3.568; p < 0.001) are over-represented compared with middle-aged drivers. Since no information is available on the age split of total SB drivers in Alberta, no firm conclusion can be drawn on over-representation of different SB driver groups in crashes. However, the result may be attributed to the operational characteristics of SBs such as decelerating or accelerating to or from stops more frequently than other bus drivers. This situation is complicated by frequent lane changes and merges they make to pick up and discharge passengers. Since younger drivers are less experienced and less skillful, while older drivers may have reduced perceptions and driving abilities, they are over-represented in SB crashes.

Driver actions are also found to contribute to more than 90% of road crashes (Rumar 1985). To conceptualize, two measures of inappropriate driving behaviors (aberrant driver behavior) are considered: errors and violations. Surprisingly, with respective coefficients of 0.606 and 0.616, which are statistically significant, both behaviors are found to be over-represented for SB drivers. Attitudes toward rule violation are identified by Rundmo (2000) as an important predictor of on-the-job risk behavior, and this relationship may also hold for SB driving. The over-representation of driving error of SB drivers may be attributed to in-vehicle distractions of SB drivers from their young passengers. McEvoy et al. (2006) identifies driver distraction inside the vehicle as one of the significant causes of road crash.

Furthermore, from the parameter estimates and the odd ratio ($\beta = 0.332$; $p < 0.001$; OR = 1.394), back center collisions are found to occur more often in SB collisions. When the center of the back of an SB is the principal point of impact in a collision, the SB is likely rear-ended by the vehicle following it. This is identified by Yang et al. (2009) as a major fault of drivers of other vehicles involved in crashes with SBs. Rear-end crashes are also found to be the main primary event in SB collisions in Alberta by Optus Hamilton (2008).

Stop (OR = 1.628; $p < 0.001$) and yield (OR = 2.052; $p < 0.01$) controlled intersections are likely to be locations of SB crashes, whereas traffic signal controlled intersections (OR = 0.868; $p = 0.078$) are less likely to experience SB crashes. As discussed earlier, SBs operate more frequently in residential areas characterized by close-packed local access points with stop/yield signs rather than traffic signals. The increased likelihood of SB crashes at these locations may also result from lower compliance with stop/yield sign regulations than traffic signals (Chipman 2004).

CONCLUSION

This study examines the contributing factors delineating SB crashes from crashes involving other buses. It uses a binary logit model and crash data from 1999 to 2008 for Alberta, Canada. The results show that relative to other types of buses, SB collisions are more likely to occur during the morning and afternoon peaks, in rural areas, and involve rear-end collisions by other vehicles or backing maneuvers. They are also likely to occur more on snowy road surfaces and at intersections controlled by stop or yield signs. Furthermore, SB collisions are more likely to involve female drivers, drivers under 25 or over 65 years old, are less likely to result in casualties, involve multiple vehicles, or result from passing or sideswiping collisions. They are also less likely to occur during the summer, on weekends, under hail/sleet/snow weather conditions, and at signalised intersections.

Although most of the results are consistent with the proposed analytical framework and hypotheses, two findings should be highlighted. First, passenger or driver injury is less prevalent in SB crashes than non-SB crashes due to low posted speeds on local roads where they mostly operate, and the implementation of SB improvement programs in Alberta. Second, compared with non-SB drivers, SB drivers are more likely to have committed traffic violations or made errors that resulted in collisions. This finding is in contrast with expectations and the hypotheses. More importantly, it is a cause for concern since scarce resources have been devoted to developing SB driver improvement programs in Alberta, and parents expect to have safe SB drivers. Hence, existing SB driver training and hiring processes should be reviewed and enhanced to reduce traffic violations and driver errors. In addition, as suggested by the results, SB safety awareness programs should be implemented and supplemented by traffic regulation enforcement programs at high-risk locations to minimize traffic violations.

Endnotes

1. PayScale. "PayScale Canada, Bus Drivers, School Wages, Hour Rates", available online at http://payscale.com/research/CA/job=bus_driver, _school/Hourly_Rate, accessed 30/4/2012.

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Equipment Replacement Decision Making: Opportunities and Challenges

by Wei (David) Fan, Mason D. Gemar, and Randy Machemehl

The primary function of equipment managers is to replace the right equipment at the right time and at the lowest overall cost. In this paper, the opportunities and challenges associated with equipment replacement optimization (ERO) are discussed in detail. First, a comprehensive review of the state-of-the art and state-of-the practice literature for the ERO problem is conducted. Second, a dynamic programming (DP) based optimization solution methodology is presented to solve the ERO problem. The Bellman's formulation for the ERO deterministic (DDP) and stochastic dynamic programming (SDP) problems are discussed in detail. Finally, comprehensive ERO numerical results and implications are given.

INTRODUCTION

As assets age, they generally deteriorate, resulting in rising operating and maintenance (O&M) costs and decreasing salvage values. Furthermore, newer assets that are more efficient and better at retaining their value may exist in the marketplace and be available for replacement. The conditions of deterioration and technological changes motivate public and private agencies that maintain fleets of vehicles and/or specialized equipment to periodically replace vehicles composing their fleet. This decision is usually based upon a desire to minimize fleet costs, which typically include the acquisition, operating and maintenance cost, and salvage value over a definite or infinite horizon.

Much research has been undertaken in equipment replacement optimization (ERO), including the Texas Department of Transportation's (TxDOT) ongoing equipment replacement optimization efforts. A detailed review of the state-of-the art and state-of-the-practice literature of the ERO problem and commercial fleet management systems currently available worldwide is available elsewhere[1]. That review shows that previous research efforts made can be classified into and solved using three solution approaches.

The first is the Minimum Equivalent Annual Cost approach (EAC). In this approach, the most basic ERO problem is studied under the assumption of no technological change over an infinite horizon (i.e., the equipment is needed indefinitely). This assumption is sometimes referred to as "stationary cost" by some researchers[1] in the sense that an asset is replaced with the purchase of a new, identical asset with the same cost. Under this assumption, the optimal solution to the infinite-horizon equipment replacement problem with stationary costs is to continually replace an asset at the end of its economic life. Once determined, the asset should be continuously replaced at this age under the assumption of repeatability and stationary costs.[1]

The second is the Experience/Rule-based approach, which is used in many state DOTs to make keep/replacement decisions for equipment, particularly during the early stages of ERO implementation. For example, TxDOT uses threshold values for age, equipment use, and repair cost as inputs for replacement (TxDOT Equipment Replacement Model - TERM 2004). This approach can work well for the fleet manager under certain circumstances. For example, current threshold values for dump trucks with tandem rear axles for age, use, and repair cost are 12 years, 150,000 miles, and 100%, respectively. As a result, a State Series 990d dump truck with tandem rear axles, a gross vehicle weight of more than 43,000 pounds, which is 12 years old, is considered as having accumulated 150,000 miles of use and repair costs of more than 100% of the original purchase cost (including net adjustments to capital value). Despite its simplicity, the use of this rule depends heavily upon the fleet manager's engineering judgment and experience with ERO.

The third is the Dynamic Programming (DP) approach in which the solution of continuously replacing an asset at the end of its economic life based on the minimum EAC method is optimal only under the assumptions of an infinite horizon and stationary costs. However, many situations occur in practice in which an asset is required for a finite length of service (i.e., finite horizon). In particular, if the costs (including operating and maintenance cost and salvage value) are age based, assuming constant or predetermined utilization over a finite horizon, the DP approach is commonly used to solve the ERO problem. An example that uses the DP approach can be seen in Nair and Hopp (1992). Recently, Richardson et al. (2013) used a new real options approach to solving the optimized asset replacement strategy in the presence of lead time uncertainty.

There have been numerous researches on ERO with finite time horizon using the Deterministic Dynamic Programming (DDP) approach (Hartman and Murphy 2006, Hartman and Rogers 2006, Hillier and Liberman 2005, Wolsey 1998, Nemhauser and Wolsey 1999). However, almost all previous researches are devoted to the DDP solution formulation and its limited applications to extremely simplified case studies and/or small examples. To the best knowledge of the authors, there have been no research efforts made so far (except Fan et al. 2012a, 2012b, and Figliozzi et al. 2011) to apply such DP approaches to solving the real-world ERO problem. In previous research, a comprehensive DP-based optimization solution methodology has been developed to solve the ERO problem. The developed ERO software consists of three main components: a SAS Macro-based Data Cleaner and Analyzer, which undertakes the tasks of raw data reading, cleaning, and analyzing, as well as cost estimation and forecasting; a DP-based optimization engine that minimizes the total cost over a defined time horizon; and a Java-based Graphical User Interface (GUI) that takes parameters input by users and coordinates the Optimization Engine and SAS Macro Data Cleaner and Analyzer.

When using the DDP approach, both vehicle usage and annual operating and maintenance costs are assumed to be constant or predetermined. However, due to randomness in real operations, these expected equipment utilizations are not normally realized in practice, thus invalidating the replacement optimization decisions in some aspects.

The stochastic dynamic programming (SDP) approach is undoubtedly the preferred approach to solving the ERO problem because it can explicitly consider the uncertainty in vehicle utilization and the annual operating and maintenance cost accordingly. Meyer (1971), perhaps due to computational constraints, is one among the very few to study the ERO problem under uncertainty. With advances in computing technology, a lot of research has been done to examine the ERO problem under uncertainties during the past decade, as can be seen in Hartman and Rogers (2006). However, none of these previous researches, except Fan et al. (2012b) and Figliozzi et al. (2011), uses real-world fleet cost/usage data, and all are limited and based on small examples. As a result, many underlying characteristics of the ERO SDP problem have yet to be explored and identified. To the best knowledge of the authors, this is the first ERO SDP software that is targeted at a real-world application (using TxDOT's current fleet data) and can explicitly consider uncertainty in vehicle utilization and annual operating and maintenance cost. This software is very general and can be used to make broad statements regarding the ERO problem. Nonetheless, it demonstrates the software's promising feasibility for large-scale applications. When enough cost/mileage data are collected, the SDP-based optimization solution can be of immediate use and will yield substantial cost savings for years to come in the fleet management industry worldwide.

ERO MODEL FORMULATION

General DP Characteristics

Following Bellman (1995), the basic features that characterize DP solution algorithms can be presented as follows: The problem can be divided into stages with a policy decision required at each stage. The stages are usually related to time and are often solved by going backwards in time. Each stage has a number of states associated with it. The decision at each stage transforms the current state at this stage to a state associated with the beginning of the next stage (possibly with a probability distribution applied). The solution procedure is designed to find an optimal policy for the overall problem, i.e., a prescription of the optimal policy decision at each stage for each of the possible states. Given the current state, the optimal policy decision for the remaining stages is independent of decisions made in previous stages. The solution procedure begins by finding the optimal policy for the last stage. A recursive relationship is available to traverse between the value of the decision at a stage N and the value of the optimum decisions at previous stages N+1. When using the recursive relationship, the solution procedure starts at the end and moves backward stage by stage – each time finding the optimal policy for that stage – until the optimal policy starting at the initial stage is found (Bellman 1995, Bellman 2003, Bertsekas 2001, Wagner 1975, Waddell 1983, Hartman 2005, Hartman and Murphy 2006).

DP can generally be classified into two categories: DDP and SDP. For DDP, the state at the next stage is completely determined by the state and policy decision at the current stage. In SDP, the state at the next stage is not completely determined by the state and policy decision at the current stage. Rather, there is a probability distribution applied for what the next state will be. However, the probability distribution is still determined entirely by the state and policy decision at the current stage (Bellman 2003, Wagner 1975, Meyer 1971). In SDP, the decision maker's goal is usually to minimize expected (or expected discounted) cost incurred or to maximize expected (or expected discounted) reward earned over a given time horizon.

DP Model Formulation

The TxDOT fleet manager identifies equipment items as candidates for equipment replacement one year in advance due to the fact that generally one year is required to allow sufficient time for procurement and delivery of a new unit of equipment. Since the TxDOT fleet manager makes decisions as to whether to keep or replace a piece of equipment at the beginning of each year, it is very natural to consider each year a stage. As a result, the year count (or index) is the stage variable in this paper and the age of the equipment in service at the beginning of each year is the state variable. The TxDOT fleet manager highly recommends that all equipment be salvaged at the end of a planning horizon of 20 years. In other words, it is assumed that an equipment unit will be kept no longer than 20 years. It is expected that the value of the planning horizon selected by the fleet manager may have some impacts on the equipment optimal keep/replacement decisions. However, it is also believed that 20 years is a very reasonable value and is therefore highly recommended for ERO problems of state DOTs.

The equipment purchase cost model is year-based, the annual operating and maintenance cost and the usage of the equipment unit are both age-based, and the salvage values are dependent upon both the model year and equipment age. All these data come from SAS as outputs of the SAS macro-based Data Cleaner and Analyzer and act as inputs to the DDP-based optimization engine. Moreover, it is realized that it is standard practice to allow for discounting of future costs in any DDP model and solution process. Put another way, solving the ERO problem using the dynamic programming approach requires all costs (such as annual operating and maintenance costs, including all repairs, regular maintenance and down time penalty costs, and salvage values, as well as purchase costs of the new model year). At each stage, such costs must be converted from the equipment model year (for the equipment purchase cost) and/or calendar year (for annual operating and maintenance costs and salvage value) to a benchmark year using an inflation rate. Such calculations for the discounting of future costs have been successfully performed.[1]

DP SOLUTION APPROACH

Bellman's Formulation for the ERO DDP Problem

Bellman (1995, 2003) introduced the first DDP solution to the finite horizon equipment replacement problem where the age of an asset defines the state of the system with the decision to keep or replace an asset made at the end of each period (stage). This paper implements the Bellman DDP approach so that the solution caters to TxDOT's needs in solving the ERO problem.

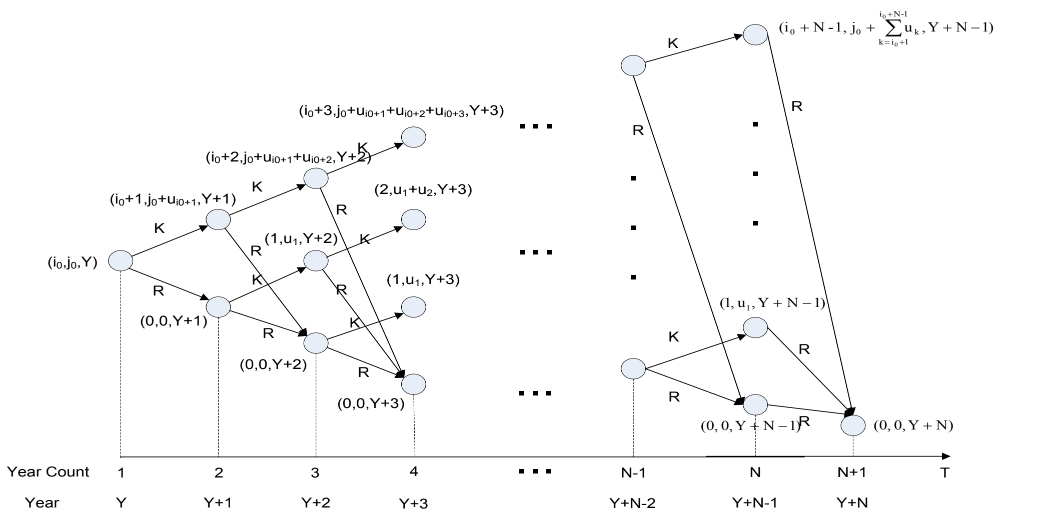
In a typical Bellman network, each node represents the age and the usage (i.e., mileage/hours) of the asset at that point in time, which is also the state space of the model. Each arc represents the decision to either keep (K) or replace (R) an asset. Keeping the asset connects nodes n (i.e., n-year-old) and n+1 (i.e., n+1-year-old) while replacing the asset is shown by an arc connecting n and zero. An optimal policy with this model, in the form (K, K, R, K, K, …), gives the optimal decision at the beginning of each year. If an asset can be retained for a maximum of periods, then the maximum number of states in a period is N. For an N-period problem, since there are a maximum of two decisions for any state, the problem can be solved using the following calculation: O (State of year 1 + State of year 2 + … + State of year N) = O (1 + 2 + 3 + … + N + 1) = O($\frac{N(N+1)}{2}$+1) where O represents computer complexity. Therefore, the computer complexity of Bellman's algorithm is O(N^2). Again, detailed information about Bellman's equation for the ERO DDP problem can be seen elsewhere.[1]

Bellman's Formulation for the ERO SDP Problem

When Bellman's approach is used in the SDP method to solve an ERO problem, a phenomenon, commonly termed "curse of dimensionality," appears. For example, the ERO SDP solution procedure, without scenario reduction treatment, has a general state-space issue that can result in exponential growth in computer memory and software computational time with increases in time horizon. Careful consideration and special treatments have been used to resolve these issues, and the computer complexity for stochastic dynamic programming is still O(N^2) using the special treatment methods developed by Fan et al. (2012b).

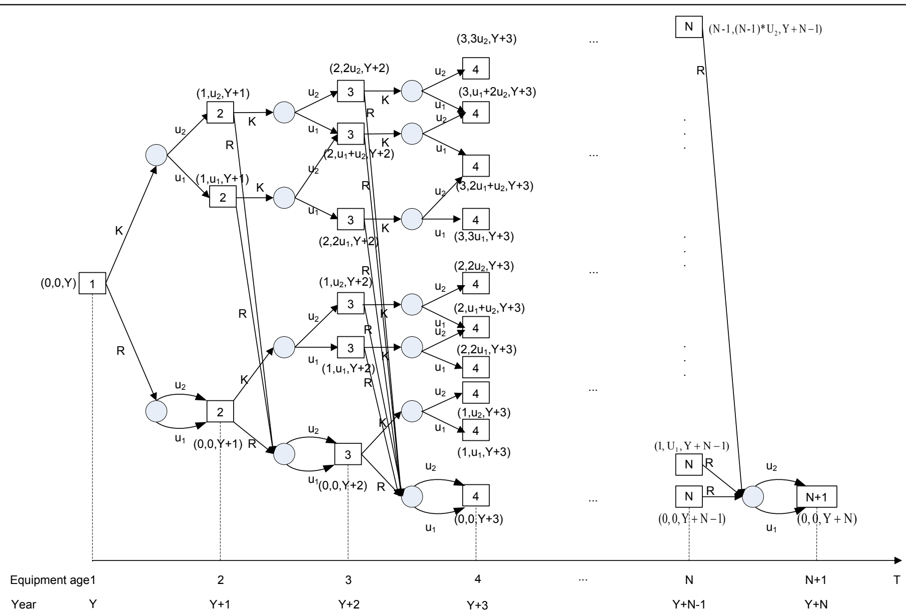
Figure 2 shows a complete "Keep-Replace" Bellman formulation example starting with a brand-new equipment unit for the ERO SDP problem, with uncertainty in vehicle utilization for the SDP-2Level case, after conducting the scenario reduction treatment. In Figure 2, the square nodes represent the decision to either keep or replace the equipment unit. The circular nodes represent chance nodes, as the equipment utilization level is uncertain and the path taken from these nodes defines the cumulative equipment utilization in the next stage. The path taken from the circular nodes are defined as and which represent two feasible (i.e., the high and low) equipment utilization levels. Additionally, all nodes at time N are connected to a dummy node at time N+1, which represents the salvage value of the equipment unit after the final stage of the finite horizon problem. It should also be noted that the total cost would include the purchase cost, the expected annual operating and maintenance cost, and salvage value, as previously mentioned.

Figure 1: Bellman's Formulation



K – Keep asset
R – Replace asset
Note:
a. $(i_0 + N - 1, j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k, Y+N-1)$ represents the status of a vehicle which is $(i_0 + N - 1)$-year old with its accumulative mileage being $(j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k)$ at the beginning of year $(Y+N-1)$. u_k denotes the usage during the year at the end of which the equipment becomes k-year old. Similar notation follows.
b. The salvage value is associated with "R" decision. The decision is made at the beginning of each year where the starting node is located. The salvage value is referred to as the value of equipment age at the end of that year. The operating/maintenance cost associated with "K" decision is related to the equipment age at the end of that year.

Figure 2: SDP Formulation for ERPO Under Asset Utilization Uncertainty: Two-Level Case with Scenario Reduction Treatment



K – Keep asset
R – Replace asset

Note:
a. (i, U_j, Y) represents the status of a vehicle which is i-year old with its accumulative mileage used being U_j during the i years at the beginning of year Y. Similar notation follows.
b. The salvage value is associated with "R" decision. The decision is made at the beginning of each year where the starting node is located. The salvage value is referred to as the value of equipment age at the end of that year. The operating/maintenance cost associated with "K" decision is related to the equipment age at the end of that year.

SOFTWARE DEVELOPMENT AND FUNCTIONALITIES

SDP Computer Implementation Techniques

To successfully implement the Bellman formulation to solve the ERO SDP problem, an efficient and effective data structure is designed and then implemented by developing Java computer programs. The model year-based equipment purchase cost, the equipment age- and model year-based salvage value, and the equipment age- and mileage-based annual operating and maintenance cost data, along with corresponding probability distribution for each year that come from SAS are read and processed by the Java codes through three steps/layers within the optimization engine. The first layer is reading the equipment class code, the second layer is reading the equipment age, and the third layer is reading the equipment utilization and associated probability (to accommodate the different equipment utilization levels). A series of dynamically allocated arrays are developed to store the data[1]. The Bellman approach, as presented earlier, is then solved backward and the recursive functions are called efficiently.

SDP Software Development and Functionalities

The developed DDP software considers two approaches for the ERO problem: First, it assumes that the “current trend” continues. That is, it uses all the information from the current TERM data that are “error- and outlier-free” and assumes that the same trend will continue for future years. For example, the current TERM data show that equipment utilization decreases as equipment gets older and therefore it is assumed that this trend will continue[1]. Second, it assumes “equal utilization.” That is, it takes the average mileage across all equipment with the same class code and uses this number for the utilization of all equipment during that year. Even with this, it is noteworthy that year-to-year utilization for the same class code can be different. In subsequent sections, numerical results are presented to show an example of the differences in the equipment keep/replace decisions between these two approaches.

Many other functions have been incorporated into the DP-based ERO software, including the following: The software allows the user to specify budget constraints, as well as the time window that the programming will use during optimization. The software allows users to selectively “clean the data” by removing missing data related to any cost and mileage variables and outliers associated with any non-missing data. And the users can run the software using SAS automatically generated cost data or use editable cost data that they provide manually at the beginning of each year. The user can choose from several different approaches, namely: current “cost trend” or cost “equal utilization” (as explained earlier in this section), DDP or SDP, and the Bellman (1995, 2003) or Wagner (1975), all mentioned and defined before. The user can also choose to delay the equipment replacement or replace it early by specifying a positive or negative delay time. The software can also run an optimization on any individual used piece of equipment from a specific class code, on all equipment units from one specific class code or from class codes, or on brand new equipment units from either one specific class code or all class codes. The software gives an EXCEL report for the cost savings by comparing the optimal solution with the benchmark rules, and it provides an EXCEL report summarizing the cost savings by comparing the optimal solution with the “delay by N years” option or the “ignore the optimized decision” option. Finally, users can add new annual TERM data at the beginning of each year and make dynamic keep/replace decisions for any chosen class code or equipment unit.

OPPORTUNITIES AND CHALLENGES

The developed ERO solution software in this paper is very general and can be used to make optimal keep/replace decisions with or without uncertainty in vehicle utilization for both brand-new and used vehicles, both with or without annual budget considerations. In other words, the methodology can be used to: provide a general guide for the equipment keep/replacement decisions (i.e., how many years to keep) for a particular class code containing brand-new equipment without considering any budget constraints; and select equipment units for annual replacement from a solution space that is composed of all the candidate equipment units that are eligible for replacement based on the annual budget and other constraints, if any. Also, it should be noted that all numerical results are essentially dependent upon the specific class code chosen. However, after comprehensive testing, it was found that numerical results of all class codes seem to follow similar patterns and exhibit some shared general characteristics. In this regard, the following section uses the real TxDOT TERM data (TERM 2004) and describes some interesting and representative numerical results using two class codes, 420010 and 520020, as an example for light vehicle and heavy vehicle classes, respectively. Related characteristics are discussed as follows.

Opportunities

The computational time of the ERO software for all class codes and each solution approach was examined. It was found that the computational time is very uniform for the DDP and SDP 2-Level approaches and it takes an average of 10 seconds for the software to provide the best optimized decision for each class code. It takes a total of about 32 minutes to loop through all (i.e., 194) class codes and output all optimized solutions in an EXCEL file for the "current trend" or "equal utilization" approach. However, the SDP 3-Level approach appears to be less uniform and most class codes take more time to run; the average for this approach was nearly 30 seconds for the ERO software to provide the best optimized decision for each class code with probabilistic vehicle utilization. Therefore, it takes a total of about 97 minutes to loop through all (i.e., 194) class codes and output all optimized solutions in an EXCEL file for the "current trend" approach in which the probability distribution of the vehicle utilization is forecasted based on the historical data.

A comparison of the quality of the DDP solution, the SDP 2-Level and 3-Level optimization solutions, and the current benchmark solutions for class codes 420010 and 520020 is given in Table 1. As can be seen, the objective function values (represented in dollar value) for each DP approach are smaller (more desirable) than for the corresponding benchmark solutions for both class codes. This is expected because each DP approach ensures that all solution paths (which certainly include the current purely experience-based replacement benchmark solution) are explored by solving backward. This guarantees that the best solution is also found by selecting the solution path with minimum total cost over the definite horizon (determined by the benchmark year).

In addition, the total cost of the benchmark solutions for the DDP, SDP 2-Level, and SDP 3-Level approaches are all different. This is expected because the DDP approach uses the class code-level cost/mileage forecast for all future years to calculate the benchmark decision year. On the other hand, both SDP approaches generate and use cost/mileage forecasts for each individual class code and all the vehicle utilization levels (low-high for 2-Level, or low-medium-high for 3-Level) and their associated probability distributions for all future years to determine the benchmark decision year. This can cause the expected cost/mileage data to be slightly different between the different solution approaches.

As one can see from Table 1, using class code 420010 with the "current trend" approach as an example, the SDP 2-Level approach results in the most savings and suggests five replacements over the 20-year window, while the benchmark solution suggests replacement at years 10 and 20 only. While the SDP 3-Level solution and the DDP solution offer similar replacement strategies, the

Table 1: Solution Comparisons Between DDP, SDP, and Current Benchmark Solutions for Class Codes 420010 and 520020

		Year	DDP Approach				SDP 2-Level Approach				SDP 3-Level Approach			
			DDP Solution		Benchmark Solution		SDP Solution		Benchmark Solution		SDP Solution		Benchmark Solution	
			Decision	Cost	Decision	Cost	Decision	Cost	Decision	Cost	Decision	Cost	Decision	Cost
		1	K	$2,881.39	K	$2,881.39	R	$5,269.29	K	$2,469.76	K	$2,469.76	K	$2,469.76
		2	R	$9,050.29	K	$3,320.66	R	$6,101.20	K	$3,448.38	R	$8,794.86	K	$3,065.23
		3	K	$2,881.39	K	$3,782.13	K	$2,469.76	K	$3,696.17	K	$2,469.76	K	$3,724.82
		4	K	$3,320.66	K	$4,256.11	K	$3,448.38	K	$4,038.96	K	$3,065.23	K	$4,198.20
		5	K	$3,782.13	K	$4,732.92	K	$3,696.17	K	$4,503.90	K	$3,724.82	K	$4,783.81
		6	K	$4,256.11	K	$5,202.88	K	$4,038.96	K	$5,070.60	R	$15,601.30	K	$4,967.72
		7	R	$17,989.34	K	$5,656.32	R	$17,760.33	K	$5,556.50	K	$2,469.76	K	$5,478.87
		8	K	$2,881.39	K	$6,083.55	K	$2,469.76	K	$6,007.50	K	$3,065.23	K	$5,779.37
		9	K	$3,320.66	K	$6,474.89	K	$3,448.38	K	$6,474.89	K	$3,724.82	K	$6,151.15
		10	K	$3,782.13	R	$25,673.63	K	$3,696.17	R	$25,478.75	K	$4,198.20	R	$25,413.79
		11	K	$4,256.11	K	$2,881.39	K	$4,038.96	K	$2,469.76	K	$4,783.81	K	$2,469.76
	420010	12	K	$4,732.92	K	$3,320.66	K	$4,503.90	K	$3,448.38	R	$21,279.03	K	$3,065.23
		13	R	$21,887.57	K	$3,782.13	R	$21,755.29	K	$3,696.17	K	$2,469.76	K	$3,724.82
		14	K	$2,881.39	K	$4,256.11	K	$2,469.76	K	$4,038.96	K	$3,065.23	K	$4,198.20
		15	K	$3,320.66	K	$4,732.92	K	$3,448.38	K	$4,503.90	K	$3,724.82	K	$4,783.81
		16	K	$3,782.13	K	$5,202.88	K	$3,696.17	K	$5,070.60	K	$4,198.20	K	$4,967.72
		17	K	$4,256.11	K	$5,656.32	K	$4,038.96	K	$5,556.50	K	$4,783.81	K	$5,478.87
		18	K	$4,732.92	K	$6,083.55	K	$4,503.90	K	$6,007.50	K	$4,967.72	K	$5,779.37
		19	K	$5,202.88	K	$6,474.89	K	$5,070.60	K	$6,474.89	K	$5,478.87	K	$6,151.15
		20	R	$26,202.97	R	$29,674.69	R	$26,103.16	R	$29,479.81	R	$27,230.39	R	$29,414.86
			Total	$135,401.15	Total	$140,130.02	Total	$132,027.48	Total	$137,491.88	Total	$131,565.38	Total	$136,066.51
			Cost Savings	$4,728.87			Cost Savings	$5,464.40			Cost Savings	$4,501.13		
Classcode		1	K	$1,865.53	K	$1,865.53	K	$1,865.53	K	$1,865.53	K	$1,865.53	K	$1,865.53
		2	K	$2,915.71	K	$2,915.71	K	$2,915.71	K	$2,915.71	K	$2,915.71	K	$2,915.71
		3	K	$3,916.86	K	$3,916.86	K	$3,916.86	K	$3,916.86	K	$3,916.86	K	$3,916.86
		4	K	$4,864.60	K	$4,864.60	K	$4,864.60	K	$4,864.60	K	$4,864.60	K	$4,864.60
		5	K	$5,754.55	K	$5,754.55	K	$5,754.55	K	$5,754.55	K	$5,754.55	K	$5,754.55
		6	K	$6,582.32	K	$6,582.32	R	$39,399.23	K	$6,582.33	K	$6,582.32	K	$6,582.32
		7	K	$7,343.55	K	$7,343.55	K	$1,865.53	K	$7,343.55	K	$8,567.48	K	$8,567.48
		8	K	$8,033.85	K	$8,033.85	K	$2,915.71	K	$10,042.31	K	$8,033.85	K	$8,033.85
		9	R	$47,607.00	K	$8,648.84	K	$3,916.86	K	$10,090.31	R	$47,607.00	K	$8,648.83
		10	K	$1,865.53	K	$9,184.14	K	$4,864.60	K	$11,152.17	K	$1,865.53	K	$8,309.46
		11	K	$2,915.71	R	$52,129.15	K	$5,754.55	R	$53,735.05	K	$2,915.71	R	$49,987.96
	520020	12	K	$3,916.86	K	$1,865.53	K	$6,582.33	K	$1,865.53	K	$3,916.86	K	$1,865.53
		13	K	$4,864.60	K	$2,915.71	R	$47,495.25	K	$2,915.71	K	$4,864.60	K	$2,915.71
		14	K	$5,754.55	K	$3,916.86	K	$1,865.53	K	$3,916.86	K	$5,754.55	K	$3,916.86
		15	K	$6,582.32	K	$4,864.60	K	$2,915.71	K	$4,864.60	K	$6,582.32	K	$4,864.60
		16	K	$7,343.55	K	$5,754.55	K	$3,916.86	K	$5,754.55	K	$8,567.48	K	$5,754.55
		17	K	$8,033.85	K	$6,582.32	K	$4,864.60	K	$6,582.33	K	$8,033.85	K	$6,582.32
		18	K	$8,648.84	K	$7,343.55	K	$5,754.55	K	$7,343.55	K	$8,648.83	K	$8,567.48
		19	K	$9,184.14	K	$8,033.85	K	$6,582.33	K	$10,042.31	K	$8,309.46	K	$8,033.85
		20	R	$60,198.47	R	$57,327.35	R	$53,674.70	R	$58,768.83	R	$58,057.28	R	$57,327.35
			Total	$208,192.39	Total	$209,843.42	Total	$211,685.59	Total	$220,317.24	Total	$207,624.37	Total	$209,275.40
			Cost Savings	$1,651.03			Cost Savings	$8,631.65			Cost Savings	$1,651.03		

difference in savings comes from the difference in the expected costs associated with each approach; these results indicate that using the developed SDP-based ERO software can significantly improve the replacement procedures and can result in substantial cost savings every year. Specifically, for class code 420010, the estimated savings is about $5,464.40/20 = $273.22 per year for a single piece of equipment. For class code 520020, the SDP 2-Level solution estimates the cost savings with replacement for year six, 13, and 20 as $8,631.65/20 = $431.58 per year, which is much greater than either the DDP or SDP 3-Level solutions. The average of the cost savings for both class codes is estimated at ($273.22 + $431.58)/2 = $352.40 per year. Considering that there are 194 class codes used by TxDOT and on average each class code includes 84 pieces of equipment, a cost savings of $352.40*194*84 = $5,742,710.4 might be expected. As can be seen from Table 1, a significant cost savings also of $2,506,389.98 for the SDP 3-Level approach can be estimated using the same method of calculation. Therefore, one might expect a cost saving of several million dollars annually for the agency using the SDP approaches.

The results provided here were obtained without explicitly considering the annual budget constraints of government agencies and private fleet providers. However, the methodology developed in this paper can be used to select equipment units for annual replacement based on annual budget and other possible constraints specified by the fleet manager. To solve the ERO problem under such constraints, the following steps are required.

First, the cost of not replacing an equipment unit when it should be replaced is estimated by comparing the total cost of the optimal solution to the minimum total cost incurred when delaying the replacement of equipment by a certain number of years. The increases in cost are quantified for each feasible replacement year and are used as inputs to the second round of optimization. Next, the second round of optimization is used to select the equipment units for annual replacement from all equipment units that are eligible for replacement. The main objective of this step is to maximize the benefits produced and include a mixture of both TxDOT's short-term and long-term interests. Preliminary results indicate that when an annual budget of $15 million is assumed to be allocated and used, a significant amount of cost savings can be estimated by applying the solution methodology developed in this paper to optimize TxDOT's equipment replacement in the current fleet existing in the TxDOT Equipment Replacement Model (TERM) data.

Challenges

After conducting comprehensive testing, all three approaches have produced promising results and can yield significant cost savings compared with the current TxDOT benchmark decision process. Because the probabilistic nature of vehicle utilization is explicitly considered, the formulated SDP approach appears to be more practically feasible than the DDP approach. However, the lack of large enough and dependable data sets for some class code/equipment units may prevent the SDP software from generating as reliable a solution as possible. In this regard, the SDP approach is still in somewhat of an early development stage and will be more promising for a future application as this line of research matures and the data collection effort progresses. The impact of uncertain future purchase cost, down time cost, and operating and maintenance cost on the ERO keep/replace decision and its total cost also need further investigation.

SUMMARY AND FUTURE RESEARCH

In this paper, a comprehensive review of the state-of-the art and state-of-the practice literature for the equipment replacement optimization (ERO) problem is first conducted. A dynamic programming (DP) based optimization solution methodology is then presented to solve the ERO problem. Bellman's formulation for the ERO deterministic (DDP) and stochastic dynamic programming (SDP) problems are discussed in detail. Finally, comprehensive ERO numerical results and implications are given along with the opportunities and challenges associated with the equipment replacement optimization problem. The software's computational time and solution quality have been demonstrated to be very promising and encouraging, and substantial cost-savings are estimated using this ERO software. The computational experience with the ERO problem also indicates that some challenges with data collection efforts need to be met in the future. Other issues with forecasting future purchase cost, the down time cost, and operating and maintenance cost must also be addressed. As this line of research matures and data accumulate, the software can be of immediate use to provide even more reliable and better results.

Endnotes

1. This paper draws from the following previous researches of the authors: Fan, et al. (2011; 2012a, b) to provide a detailed discussion and analysis of equipment replacement optimization.

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Measuring Spatial and Temporal Market Structure in a Transportation Sector: For-hire Grain Trucking on the Alberta-Saskatchewan Border in Canada

by Andrew Laing and James Nolan

While the trucking industry across North America is now fully de-regulated, truck markets and movements are diverse enough that the level of competition in truck transportation almost certainly varies across space, commodities, and even time. Most studies of market power in transportation do not measure or account for spatial or temporal variation in levels of competition, and in addition, it is not clear to what degree such variation affects shippers. For example, there is anecdotal evidence that trucking of certain commodities in Western Canada is characterized by considerable market power that only manifests at certain times of the year. In this light, we examine both spatial aspects as well as the dynamics of rates in the medium-to-long-haul grain trucking sector in West-Central Alberta and East-Central Saskatchewan on the Canadian prairies. We attempt to characterize market power over both space and time within this regional trucking sector. This is done using a unique and detailed data set of trucking rates charged to shippers (farmers) for grain transportation to a common destination (Lloydminster, AB) from the numerous dispersed farms in the region.

To frame the unique spatial aspects of this issue, we begin by using geographic information systems (GIS) software to build freight rate contours for this trucking market through space. A set of suppositions regarding the possible shape of these contours as they relate to transportation market structure is also developed. Subsequently, a subset of the data is used to conduct an econometric estimation of short-run freight rate dynamics. These latter estimates reveal evidence of less than competitive transportation markets through time and space. Ultimately, we find that market power in trucking is not persistent within this market, but we do observe uncompetitive pricing behavior at certain times of the year. Given that trucking is deregulated, the latter finding is somewhat unexpected. We suspect that this set of conditions very likely affects trucking rates across more markets and regions than the one examined here.

INTRODUCTION

Inefficiencies in freight transportation can seriously affect industry competitiveness in today's globalized marketplace. Trucking is the most important freight mode with respect to value transported, both worldwide and within North America. Canada, with its vast geography and dispersed population, is more economically dependent upon efficient transportation systems, including trucking, than many other industrialized nations.

The trucking industry was first regulated in Canada in the 1940s as a result of pressure to protect the rail industry from this relatively new form of competition. Changes in the political and regulatory atmosphere led to substantial deregulation of the Canadian trucking industry throughout the 1980s (Woudsma et al. 1996). For example, in 2004, trucking represented just under one third of all transportation activity, employed 168,000 people, and contributed $14.8 billion to the economy (Statistics Canada 2004).

A survey of studies prepared at various times for the government of Saskatchewan reveals the importance of for-hire grain trucking, particularly in the agri-processing sector. In 1998, grain hauls by truck in the province were 17 times greater than in the 1970s on a tonne-kilometer basis (Ray Barton Associates 1998). Furthermore, hauls to processing facilities represented 1.4 billion tonne-kilometers of traffic, which is twice the level of traffic moving from farms to primary elevators. This study also found that grain deliveries peak in September and October, while reaching a low in April and May. Extended to all of Western Canada, grain movement to processors comprises about 6 billion tonne-kilometers (Trimac Consulting Services Ltd. 1999).

In Western Canada, agriculture is highly dependent on trucking for the movement of grain. Today, virtually all prairie grain is hauled via truck from the farmgate to the elevator or processor before entering the domestic or export supply chain. However, there have been surprisingly few published studies of market structure in Canadian trucking since deregulation. Furthermore, in spite of what appears to be a generally successful deregulation transition in Canadian trucking, there is continued anecdotal evidence from this sector that the level of trucking competition (as reflected in rates and service) varies noticeably across time and space. Evaluating the level and structure of competition in this sector is important because a less than competitive trucking industry ultimately leads to higher transportation costs for farmers, lowering profits in an industry that often operates on tight margins.

To address these issues, we collected trucking rate data in order to evaluate the dynamics of transportation market structure within a region where one of the primary industries is grain handling and transportation. A set of free-on-board grain trucking rate records for a canola processor located in Lloydminster, Alberta, was assembled, creating a panel of trucking rates charged to farmers for canola delivery to Lloydminster from the numerous origins (farms) in the region. To illustrate some of the unique aspects of the data and analysis, we begin by using geographic information systems (GIS) software to develop visible freight rate contours for this transportation market through space. We first discuss how these contours should look under varying market structures, and then examine in detail a set of the generated contour maps for indications of uncompetitive pricing. Subsequently, we use a detailed subset of the data to perform an econometric estimation of short-run rate dynamics in this trucking market, using impulse response analysis to assess evidence about the degree and scope of competition in this market. After interpreting and comparing the results of these approaches for the measurement of market power in transportation, a final section concludes.

LITERATURE REVIEW

Trucking in North America and Canada

Throughout much of the 20th century, the trucking industry in North America was regulated over prices, entry, and service. One common argument historically used in support of trucking regulation was that without government regulation, shippers located in rural areas would face higher rates and reduced service. An excellent review of the theory and history of trucking regulations in the United States and Canada can be found in Sloss (1970). Sloss also examines the historical differences between the trucking industry in the province of Alberta, which was generally not regulated, and that of the province of Saskatchewan, which was highly regulated up to the more recent era of deregulation.

With deregulation of the competing freight rail sector, the for-hire trucking sector was finally deregulated in both the U.S. and Canada through the 1980s (Viscusi et al. 1996; Bonsor 1995). In fact, there exists a considerable empirical literature about the U.S. experience with trucking deregulation. Most of this research indicates that deregulation was responsible for improved safety, greater efficiency, and lowered rates in the United States (Beilock and Freeman 1987; Carlton and Perloff 2005).

With respect to agricultural transportation, research on the grain elevator industry in the U.S. has evaluated the transportation characteristics of elevators in the Great Plains Region (Vachal and Tolliver 2001). Their survey of elevator managers examined their perceptions of grain trucking availability during harvest and non-harvest periods, as well as overall competition within the trucking industry. Rates were also surveyed for harvest and non-harvest periods, for distances of 50, 100, and 200 miles (80, 160, and 320 kilometers, respectively). They found that rates increased during harvest and decreased per loaded mile as distance increased. So for certain U.S. grain producing regions, evidence exists of seasonality in grain trucking rates.

One of the few Canadian-based studies that analyzed the effects of trucking deregulation was that of Woudsma and Kanaroglou (1996). Utilizing a mix of data from Statistics Canada, the authors analyzed a set of commodity groups and traffic corridors in the Ontario trucking market to determine if freight rates and service levels were consistent among urban and non-urban routes. They found no significant change in rate setting or service provision following deregulation.

Woudsma and Kanaroglou (1996) offered two possible interpretations for their unexpected results. The first possibility was that Canadian regulation was so ineffective that the removal of these regulations did not result in any significant changes to the business environment. The second interpretation was that the effects of deregulation within the trucking industry are inherently difficult to assess using aggregated data, since each corridor and commodity has its own unique characteristics. In fact, evidence for the latter was observed in the measured effects of deregulation in the Ontario provincial trucking market, where they found some commodities that were affected positively, some negatively, and some not at all by deregulation. Our research differs from their work because this analysis uses disaggregated rate data on just a single commodity moving from multiple origins to one destination. In addition, our rate data have been collected directly from the shipper and thus are less likely to contain any measurement bias.

Empirical Studies of Market Structure in Transportation Industries

De Vany and Walls (1996) proposed in their research that spatial arbitrage will affect goods prices only if there exists a flow of goods between the spatial markets. In unregulated markets, these opportunities will be exploited until delivered prices are equalized across markets and supranormal profit is dissipated – this is the classic law of one price. However, if there is no link between dispersed markets, or the flow between the two markets is restricted, then De Vany and Walls (1996) offer that goods prices will no longer be bound by these arbitrage limits and that opportunities for supranormal profit will persist.

In their work on the U.S. natural gas market, De Vany and Walls (1996) found that if their test of the law of one price failed, it occurred either because there were no physical links between markets allowing for product to flow, or there were capacity/flow constraints. Applying impulse response analysis with their time series model, they showed that when the law of one price holds, any variation in spot prices was dampened very quickly. In related work, De Vany and Walls (1999) again applied their empirical time series arbitrage framework, this time to deregulated electricity markets. The latter study also contains a discussion of seasonality issues in electricity markets. They conclude that during off-peak periods, price shocks can be absorbed in the local market, without much effect on other markets. However, during peak periods, the local market is less able to handle price shocks, and the effects ripple through the connecting markets.

Finally, Miljkovic (2001) examined pricing practices of U.S. railways by constructing an econometric model measuring freight rate convergence between regions. He tested the possibility that markets might exhibit partial adjustment (incomplete convergence) when some degree of market imperfection, such as a transportation monopoly, exists in that market. When freight rates were found to converge across regions, Miljkovic (2001) suggested that this occurred because many movements in his data set had access to competing forms of transportation, including trucking and river barges. In those cases when freight rates did not converge, he argued that this was likely due to an origin being served by a monopoly transportation provider (a railway). In the econometric portion of this research, we will use a similar specification as these authors, which will allow us to assess the speed at which freight rate shocks dissipate in various markets.

EVALUATING SPATIAL MARKET POWER AND DYNAMICS IN TRANSPORTATION

In the study of competitive markets, one of the traditional prerequisites for the existence of a perfectly competitive industry is that markets are somehow localized, with considerations of space usually subsumed in assumptions about equivalent delivered pricing, which in itself helps define the relevant market for analysis (Viscusi et al. 1996). With respect to transportation industries, it is clear that the element of space is a crucial factor in market structure. This reality renders it more difficult to identify and understand market structure in transportation markets in a traditional sense.

Since trucking route and pricing restrictions in Canada were lifted under deregulation, we would expect, *ceteris paribus*, that few constrained transportation flows should remain between these regional trucking markets. In effect, trucking firms will respond to price signals by moving excess service capacity to those markets where there are profits to be earned. This reallocation of resources in a competitive market should eventually generate a single transportation price for a comparable service (e.g., commodity, location, etc.). Alternatively, when transportation flows are constrained or restricted, such as when supply tightens during the peak-load grain movement period at harvest, we expect that transportation rates should rise due to a decrease in competitive pressure. However, in a deregulated market, trucking rates should eventually return to arbitrage-free equilibrium when these restrictions disappear. And during other times, if an abnormally high rate is observed for a particular origin/destination pairing over an extended period, it is highly likely to be an indication of reduced transportation competition in that market.

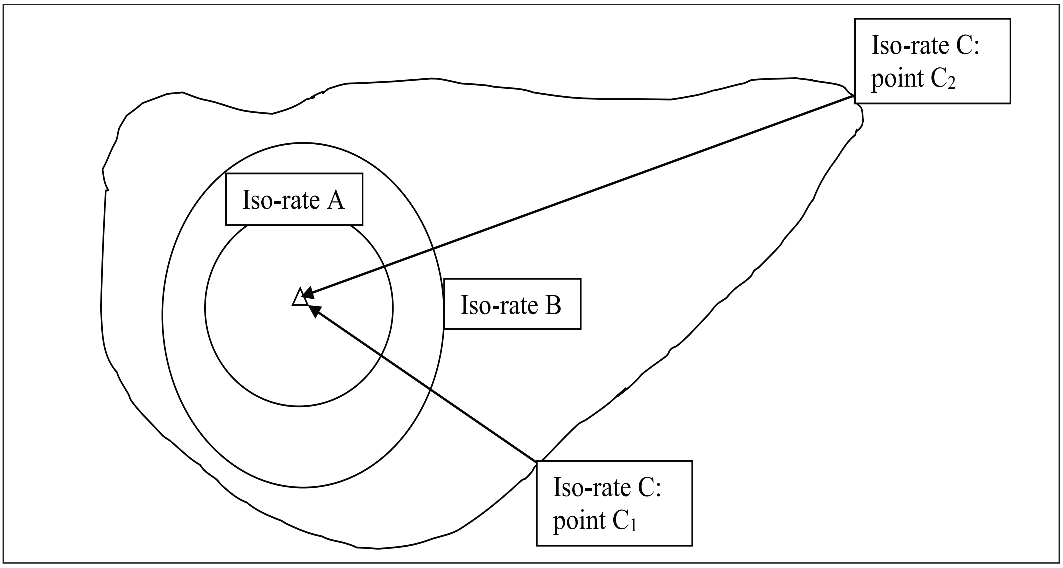
For these shippers and this market, considering off-peak periods such as the period before grain harvest, regional, and local trucking companies should be able to manage any transitory changes in transportation demand. In this case, rates may fluctuate briefly in certain markets, but these changes should not affect other origin/destination pairings to a significant degree. However, during peak movement periods, the local trucking market may not have enough capacity to meet increased demand. Therefore, not only will freight rates rise in the local market, but supply will likely be drawn in from other markets, reducing available supply, and increasing rates in those markets as well.

Rate Structures and Spatial Context - Iso-rate Contours[1]

To examine the nature and structure of competition in this regional trucking market, we begin by developing a spatial representation of the rate data. In effect, we generate a set of iso-rate, or "same-rate," contours for the trucking market using ArcInfo GIS software. As we shall see below, these contours can reveal interesting spatial patterns in the base freight rate data.[2] All iso-rates created for this study are centered on the single destination or delivery point for all freight traffic in the data set (the town of Lloydminster, Alberta).

With reference to the importance of space in transportation, the following interpretation is offered concerning the shape and relative smoothness of these transportation iso-rate contours (see Figure 1). In a competitive transportation market, transportation rates should depend mostly on cost. And since transportation cost is in most cases proportional to distance, it should be the case that competitive freight rates vary in proportion to changes in the distance between origin and destination in that transportation market. Therefore, all else being equal, freight rates set competitively should increase (decrease) equi-proportionately as distance increases (decreases) relative to a common origin or destination (i.e., the market). Regarding a mapping of rate contours, this means that a competitive transportation market should generate relatively smooth and symmetric iso-rate level curves with minimal distortions in the contour. Examples of this are shown with the hypothetical iso-rate contour representations A and B in Figure 1, each measured relative to the central origin/destination (represented by the small triangle in the figure).

Figure 1: Possible Iso-rate Shapes for Transportation



Allowing for the fact that the exact shape of iso-rates in a particular transportation market can also depend on specific geographic factors, such as the existence of impassable barriers (i.e. rivers and lakes) and the physical design of the transportation network, all else being equal, iso-rate curves generated within a competitive transportation market should approximate a smooth circular or elliptical shape. Given this supposition about the shape of competitive iso-rates, we suggest that the converse can also be the case - that marked distortions or irregularities in mapped freight rate contours that are not readily attributable to any obvious physical or geographic factors affecting route choice may instead be attributable to varying levels of competition through the transportation market at that point in time. The latter situation is shown using the stretched or distorted iso-rate C in Figure 1. Using the assumptions, the identical rate paid at the closer physical location to the origin/destination (point C_1) compared with the more distant point C_2 would be attributable to relatively less competition in the vicinity of point C_1.

Rate Dynamics Through Time and Space – Vector Autoregression

This regional trucking market is multi-faceted. Rates may depend not only on market structure, but also on long-term relationships, time, and capacity. In fact, rate setting in the sector may give rise to relationships that mask collusive and/or monopolistic behavior on the part of trucking firms. Given this, we will supplement the spatial mapping analysis with econometric estimates and impulse response analysis using a subset of the same data to identify the structure of rate dynamics associated with a set of origins (De Vany and Walls 1996). A series of vector autoregressions on trucking rates will be estimated between pairs of some key origins in the sample. Specifically, the econometric pair-wise relationships estimated have the following structure (for the analysis, all data were transformed using logarithms):

$$p_{a,t} = p_{a,t-1} + p_{a,t-n} + p_{b,t-1} + p_{b,t-n} + DI_t + DI_{t-1} + DI_{t-2} + W_t + W_{t-1} + W_{t-2} + spring + summer + winter + \mu_t$$

$$p_{b,t} = p_{b,t-1} + p_{b,t-n} + p_{a,t-1} + p_{a,t-n} + DI_t + DI_{t-1} + DI_{t-2} + W_t + W_{t-1} + W_{t-2} + spring + summer + winter + \mu_t$$

Here, $p_{(a,t)}$ is the trucking rate from origin A to destination at time T, DI is the diesel price index, and W is an averaged (monthly) wage rate for equipment operators (variable names used in the analysis are listed in Table 2 and Appendix E). The reason to include a diesel price index (see Appendix B) and the wage rate in the estimates is that these two factors alone comprise between 48% to 60% of the total operating cost for commercial trucks (Trimac Consulting Services Ltd. 2001; Bulk Plus Logistics 2002; Bulk Plus Logistics 2003; Logistics Solution Builders Inc. 2005). Since rates are almost certainly affected by significant cost variation no matter what the structure of the market, these variables need to be included in a study of rate movements at the market level.

Inclusion of these exogenous variables also prevents freight rate variance from being falsely attributed to variation at the other origin. Furthermore, lag structures in the variables are used to capture time adjustments to rates, since the rate setting process along each route at each location may not adjust immediately to changes in variable trucking costs.[3] We also selected two period lags in the exogenous variables, since it is the understanding of the authors that trucking firms in this sector typically do not adjust prices immediately in the very short term because of expected future price changes. However, we postulate that in a typical competitive operating environment, it is highly unlikely delays in rate adjustment longer than two time periods (two months in our sample) would be observed.

Subsequently, impulse response functions (or IRFs) will be generated using simulated (price) impulses or shocks for each equation pair. As a well-established graphical diagnostic technique used in VAR modeling to examine system dynamics, Schmidt (2004) offers an excellent description of impulse response estimation and interpretation. The reason we will generate IRF's in this situation is that related research in other industries has argued that due to arbitrage across markets, competitive freight rate setting processes should necessarily react to mitigate rate/price impulses or shocks relatively quickly. This means a competitive transportation market modeled with a VAR (and associated IRFs) on rates should completely dissipate a (simulated) rate shock/impulse within the short run, with the latter as defined by the data series (De Vany and Walls 1996; Wilson and Thoma 2007). Conversely, a less competitive freight rate setting will not dissipate a simulated rate shock as quickly. In the latter case, rate adjustments must be occurring in relative isolation from other markets, thus slowing or limiting the possibility of competitive price arbitrage to dissipate any supernormal profits from the rate shock.

DATA

The data used in this study were provided by a canola processor located in Lloydminster, Alberta. Sixty-eight months of transportation rate data were compiled from January 2001 to August 2006. In the analysis, the monthly rates used are averaged over that month. The data include month and year of delivery, origin, as well as the rate paid to the trucking firm for the movement. Freight rates are listed as Canadian dollars per metric tonne, and observations are all based on a common convention of 40 net metric tonnes of canola seed delivered per truck movement. While the common destination or delivery point is Lloydminster (see the detail map in Appendix A), those origins from where the product is delivered to Lloydminster are found across the expanse of East-Central Alberta to West-Central Saskatchewan.

Once assembled, a small percentage of observations were discarded, mostly due to odd sized loads or trucking rates that were flat rates. Additional supplementary data relating to costs were obtained from Statistics Canada (2006a, 2006b), including the retail diesel price index for the Prairie region, as well as the average weekly wage rate for transport and equipment operators in Alberta and Saskatchewan.

The data had to be organized in two ways. To more readily construct the maps or contours of the trucking rates around the single delivery point, the data were aggregated into quarters. Ultimately, only "spring" and "fall" (harvest) periods were mapped for this study, and industry realities (to be discussed in detail later) suggest these quarters would be most likely to show evidence of any non-competitive pricing practices. Table 1 lists the number of origins present in each period for the various iso-rate maps. With respect to the overall shape of the iso-rate maps, it is worth noting that another interesting aspect of this study is that the region possesses a very dense rural road network, typically offering several possible routings for many of the movements contained in the data set. In fact, the province of Saskatchewan has the highest road density per capita of any jurisdiction in North America (Barry et al. 1999). And while the quality of the road varies in Saskatchewan, the route choices for grain movement remain surprisingly numerous.

Table 1: Number of Locations by Season Used in the Construction of the Iso-rate Maps

	Spring	Harvest
2001	82	64
2002	48*	10*
2003	45	64*
2004	38	64
2005	82*	50
2006	45*	

* For clarity, these iso-rate maps were omitted from this analysis. However, all the iso-rate maps are available upon request from the authors.

To assemble appropriate data for the examination of rate dynamics in this industry and region, some data issues had to be addressed. We note that while there were 10,059 individual observations in the full data set (a basic summary of the complete data set is in Appendix C) associated with more than 30 origins, only seven origins were ultimately chosen for the econometric portion of the analysis because they yielded by far the most consistent rate data through the entire sample. Four of these seven origins are actually aggregates of two or three proximate origins in the original data, but this helps maintain the overall continuity of this data set. The names of the origins used in the econometric analysis of rate dynamics are listed in Table 2. In total, the chosen origins generated 3,723 observations, or 37% of the total rate data.

Table 2: Locations Selected for VAR, Variable Names (Appendix E) in Boldface

Location	Province	Distance to Lloydminster (KM/Miles)	Elevator or Farms	General Compass Direction (from Lloyd)	Total Number of Observations	Months with Observations (out of 68)
Wetaskiwin **(Weta)**	AB	266/165	Farms	W/SW	508	57
Biggar/Perdue/Asquith **(Big)**	SK	250/155	Farms	E/SE	390	49
Hamlin/North Battleford **(Ham)**	SK	151/96	Elevator	E	553	48
Allan **(All)**	SK	337/209	Elevator	E/SE	371	43
Radisson/Borden **(Rad)**	SK	210/130	Farms	E	172	39
Prince Albert/Birch Hills **(PA)**	SK	348/216	Farms	E/NE	185	38
Unity **(Uni)**	SK	164/102	Elevator	SE	1,544	37

But as shown in Table 2, none of the selected origins generated consistent observations through the full sample period. For instance, while Unity, SK generated 15% of the total data set, Unity rate data was observed in only 37 of the 68 sample months. So in order to construct a proper temporal data set for comparative analysis, non-coincident observations in time across these chosen origin pairings were discarded, as well as any missing observations. The latter process reduced the data set for the econometric analysis considerably. As an example, while Wetaskiwin and Allan as origins (to Lloydminster) generated almost 900 rate observations between them in the 68 months of raw data (see Table 2), rates from Wetaskiwin to Lloydminster and Allan to Lloydminster were observed at the same point in time (i.e., the same month) on just 38 occasions in the data (see the first entry in Table 3). Ultimately, we identified a set of such trip pairings (pairs of origins) that generated a minimum of 25 concurrent observations over the sample. This left us with 16 possible trip pairings across the region to be examined in the econometric portion of the analysis (see Table 3).

Table 3: Concurrent Observations for VAR Pairings (Origins to Lloydminster)
(Asterisk Indicates a Stable VAR Pairing)

Wetaskiwin	Allan	38		Biggar	Allan*	32
	Biggar*	43			Hamlin*	41
	Hamlin*	43			Prince Albert*	31
	Prince Albert	33			Radisson	29
	Radisson	33			Unity*	25
	Unity	26				
				Allan	Prince Albert	27
Hamlin	Allan	37			Radisson	26
	Prince Albert*	32				
	Radisson	29				

EVALUATING THE SPATIAL NATURE OF TRUCKING RATES AND DYNAMICS THROUGH TIME

Iso-rate Maps

A set of representative rate contour maps are illustrated in Appendix D, Figures 2 to 7, and we also refer the reader to the detail map in Appendix A, highlighting the location of Lloydminster and the major highway in the region, Highway 16. Each iso-rate map effectively represents a snapshot of the prevailing trucking rates at that time for travel to the plant in Lloydminster. One element that stands out about the contour maps was the distortionary influence of the main highway running through the region. Provincial Highway 16 runs east-west through Lloydminster and connects the city to major population centers in both Alberta (Edmonton) and Saskatchewan (Saskatoon). Many of the illustrated contours appear to be formed into a stretched elliptical shape centered on the highway. Since Hwy 16 is the main feeder route for traffic moving east-west in the region, this finding is not entirely unexpected. In addition, the influence of Hwy 16 on the contours might also be attributed to the fact that while high in density, much of the regional rural road network (especially in Saskatchewan) was moving into disrepair around this time (Nolan 2003). This combined effect seems to really stretch some of the iso-rate contours along the highway within Saskatchewan (see Figures 2 and 3 for example). We conclude that that local road conditions in this sector at that time must have strongly affected routing decisions.

Another interesting finding was that a number of the constructed iso-rate contours were not very smooth (round or elliptical), even accounting for the effects of Highway 16. As described earlier, a jagged contour implies that a trucking company operating from the more distant origin was paid the same rate as a trucking company moving the commodity from an origin closer to the destination, even when both shipments were made at approximately the same time. Ceteris paribus, since the more distant location necessarily generates greater transportation costs, the closer carrier moving the commodity would seem to have been over-paid (i.e., operated in a less competitive market) relative to the more distant carrier.

While of interest because this finding stands in some contrast to common perceptions about the trucking industry in general, in all cases identified in the contour data, conditions indicative of reduced transportation competition were not static and the mapped rate contours often changed markedly from one season to the next. As an example, when observing contours that would appear to indicate reduced transportation competition, such as the jagged and pointy set of contours through the eastern portion of Figure 4, if we examine the same contours one year later (Figure 5) they are much smoother by comparison, a result consistent with increasing competition over time. And conversely, we observe in Figure 6 that the iso-rates are generally smoother compared with those found in Figure 7 (again, the latter are observations from one year later), where the iso-rates are more jagged or irregular.

Our observation that iso-rate roughness did not persist and was of relatively short duration in the sample accords with an observation by DeVany and Walls (1999) with respect to electricity markets, who found that periods experiencing capacity constraints were characterized by above normal rates. For grain trucking in this region, the iso-rates seem to show that most of the time and on aggregate trucking rates were set competitively, but there were certain times and places where less competitive rates could be identified, and in most cases only transitionally. Perhaps not surprisingly, the contour maps also show that the latter situation occurred more often in times where demand for trucking services and capacity (i.e., at harvest time) would likely come under the greatest strain.

Rate Dynamics - Econometric Analysis[4]

Next, the dynamics of the 16 trucking rate origin pairings shown in Table 3 were examined in more detail using time series methods. Initial unit root testing on the data series within the origin pairs revealed that many of the series were non-stationary, so all the rate series were first differenced to achieve stationarity. Ultimately, seven data pairings stabilized for further analysis (see Table 2 and Appendix F), and the set of coefficient estimates are listed in Appendix E.[5] The VAR models estimated are labeled as Models 1 through 7, grouped in the table by common origins across the models as much as possible.

Overall, the VAR estimates account for approximately 45% of variation within the various trucking rate time series. Harvest or "fall" as defined in the study was expected to generate the highest trucking rates compared to the other seasons, since the greatest volume of grain moves at harvest time in the region. We found that several of the dummy seasonality variables had negative coefficient estimates (with six of the seven models showing this effect), meaning that time periods other than harvest were generally characterized by comparatively lower rates. We also found that diesel prices (including lags in some cases) were significant in five of the seven models, while four of these significant coefficients were positive (the expected sign). Wages were also found to be significant in four of the seven models, but only one of these coefficients was positive (the expected sign). Finally, while we must be careful not to infer too much from the estimated price coefficients, they do offer insight about the structural dynamics within each estimated system (Schmidt 2004). Observe that while every model had at least one significant own-price coefficient, only three of the seven had significant cross price coefficients. Taken together, this implies that the level of market integration varied considerably among the chosen origin pairings.

Vector Autoregression Impulse Responses

Impulse response functions are simulated responses to one standard deviation shocks to each estimated equation in VAR model and are used to analyze the ability of the estimated system to absorb and dampen out rate "shocks' over time. For the trucking rate VAR pairwise models estimated here, each impulse response graph is shown in Appendix F, Figures 8 to 14. Note that each graph shows the dampening process associated with each rate equation in the two equation systems, initiated through a simulated shock to the listed rate variable. With the exception of a single example (Figure 12 – Biggar/Allan), none of the simulated system shocks dampen very quickly. In fact, the average duration from shock to dissipation in the origin parings is approximately six to seven months.

As noted previously, relatively fast dampening of such impulses is expected within a competitive market. But leaving trucking competition considerations aside, there are other possible reasons for the extended shocks in these origin pairs. These include the restricted flow of information between trucking firms, as well as the actual rate setting process at the canola processor in Lloydminster. Since at the time there was no central market for truck freight in the region, obtaining rates from competing firms was not a simple process and involved significant transaction costs. If a certain trucking firm asked for a high or uncompetitive rate from a given origin, that information would be slow to disseminate to other trucking firms. Thus, any movement of market resources as a reaction via arbitrage would occur slowly, if at all.

The actual rate setting process at this processing facility represents an interesting study in transaction costs and also confirms that mapped distortions in the iso-rate lines were attributable to varying levels of spatial competition in the trucking sector serving the canola processor.[6] During the contracting process with sellers, the processor would offer to coordinate with trucking firms regarding on-farm pickup of the product as a convenience service. If this option was accepted, the trucking rate would be negotiated and set during this process, and was typically based on common expectations of the current market rate for truck freight. Once this contract was settled, the negotiated rate became a deduction from the final price paid to the farmer for the product. The trucking firm would be paid from this deduction, but it is important to note it was possible that the negotiated rate and actual rate paid were not the same. Of course, if the processor could find a trucking firm willing to transport the load for a lower rate than what was contracted initially, this would result in a net gain to the processor. However, incentives for the staff at the processor to try to find a lower trucking rate were not strong. This was because any profits obtained in this way were likely to be small in comparison with other possible non-transportation-related profit opportunities at the facility, while searching for lower truck freight rates had a high opportunity cost.

There is also evidence of weak market integration and diminished trucking competition between certain origins in this sub-sample (see Appendix A map) of the trucking rate data. We note that figures 8 and 13 (both associated with a Prince Albert, SK, origin) show impulses that persist relatively longer as compared with others found in the sub-sample. While the city of Prince Albert is located approximately the same distance to Lloydminster as the town of Allan, Prince Albert is not on Highway 16, like Allan. Overall, the impulse responses indicate that Prince Albert is less connected to Lloydminster than Allan or any other of the Saskatchewan origins found in the sub-sample (i.e., Unity and Biggar).

In fact, the route to travel from Prince Albert to Lloydminster is more circuitous compared with the other locations identified in the VAR analysis. Such routing issues would also likely reduce the number of trucking companies who are willing to participate in this particular market. Combined with the observation of a lower overall traffic volume (Prince Albert had the second lowest number of observations in the sample), the impulse responses would seem to buttress the fact that there were simply fewer opportunities for market arbitrage in the Prince Albert-Lloydminster market, possibly because there were simply fewer trucking companies serving it. Although not conclusive, in light of the persistent shocks present in the relevant impulse response functions, it seems that relatively less trucking competition was present in the Prince Albert to Lloydminster route during this time.

On the other hand, evidence for competitive market structure in the other regional trucking markets can be seen by examining Figures 10, 12, and 14. In each of these market pairs, at least one of the locations generated rate shocks that converged to zero relatively fast. These responses to the price shocks indicate that the chosen pair of origins was well integrated in at least one direction, meaning that competition in the market was relatively strong. In fact, the impulse responses shown in Figure 12 indicate mutual market integration, with shocks that dissipate quickly in both directions. This result is likely due to the fact that both of these particular origins (Biggar/Allan) are relatively close together geographically, so that trucking from either origin uses the same routing. In addition, both of these origins are located close to a population center (Saskatoon), meaning that shipments from either could also be serviced by trucking firms located in Saskatoon, along with the regional trucking firms. Given this, it is not surprising that greater trucking competition in these areas was identified through the impulse responses, a finding in some contrast to some of the more remote origins in the region that would likely only be served by local trucking firms.

On its own, finding that no impulse responses generated through the trucking rates were dissipated very quickly (none of them dampen in less than five months) was somewhat surprising. In fact, many argue that the trucking industry is almost hyper-competitive, and that there are simply too many trucks on the road throughout North America (Belzer 2000). What is clear is that the trucking industry as a whole is extremely competitive, meaning that any arbitrage opportunities on rates should be everywhere quickly and fully dissipated down to purely competitive levels. But since the impulse responses generated within this trucking market took on average approximately six to seven months to dissipate, it seems that portions of this particular market were not always extremely competitive all the time, as is commonly assumed.

In conjunction with the results from our iso-rate analysis, we identified variations in competition levels through space and time in what is considered by many without question to be a highly competitive industry at all times and in all places. Even considering the nature of the commodity market being served and other specific factors about the region, there were still instances and places where the de-regulated trucking market serving this region appeared to be considerably less competitive than expected. So while we conclude that perfect competition is still an appropriate economic paradigm to describe the broader North American trucking sector, we uncovered evidence showing that within the region and for this type of movement, trucking was not perfectly competitive consistently over both time and space.

CONCLUSION

This research examined the medium- to long-haul agricultural trucking sector serving West-Central Alberta and East-Central Saskatchewan. Considering some persistent anecdotal evidence about the trucking market in the region, our objective was to evaluate the level and scope of competition within this particular trucking sector over the sample period.

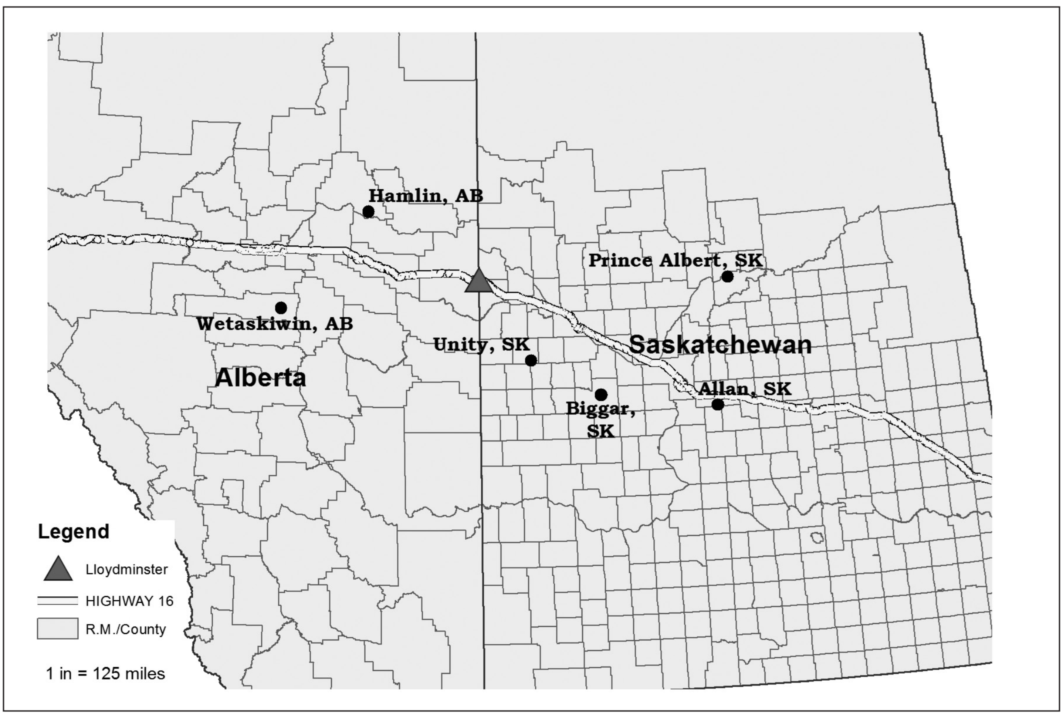
Due to the nature of the agricultural commodity being moved, iso-rate contours for spring and harvest quarters were constructed using geographic information system software. We motivated and described a set of general suppositions regarding the shape of these iso-rates in relation to market structure. While we found that some portions of the maps appear to be indicative of non-competitive pricing behaviour in relation to our expectations, these effects were not found to last very long. While an uncompetitive market structure is not persistent within this trucking sector, we did identify certain times and locations where non-competitive behavior could play an unexpectedly important role.

To buttress the mapping analysis, a sub-sample of the rate data set was used to estimate a pairwise VAR system (and associated impulse response functions) across several key origins in the region. Surprisingly, none of the impulses generated with this trucking data dissipated very quickly, a finding in contrast to what would be expected in a fully competitive market. However, the duration of the impulses was not long enough to conclude that the market as a whole was non-competitive. But on a practical level, our findings highlight concerns about the level of trucking competition that existed on at least one important transportation corridor in the region (Prince Albert-Lloydminster).

While the data used here in these analyses were extensive, additional variables would improve any future studies of spatial and temporal market power in transportation. These might include rates charged on outgoing loads, region-specific diesel prices, and trucking-specific wage rates. Extending the model to include outgoing freight rates would provide additional validity, as examining incoming loads alone cannot completely capture the nuances of this transportation market. In addition, diesel prices differ across provinces as a result of varying taxation rules and supply issues. Using province-specific rates would allow the exercise to better account for such subtle differences, while the same could be said for the use of trucking-specific wage rates. Finally, while not pursued in this preliminary analysis, it would be instructive to estimate a larger VAR system that accommodates all identified origins simultaneously. As noted above, pairwise modeling restricts the possible sources of variation within the model, and could result in omitted variable bias as a consequence. Running all locations simultaneously would remove this bias, and would give a much better idea of how rates propagate throughout the study region and not just in selected pairings.

In suggesting ways to improve the current study, consider the quote from Norton (1971): “is there any complex industry about which too much can be known?” (p.453). The grain trucking industry in this region certainly seems to fall into this category and is worthy of continued analysis.

Appendix A: Detail Map of the Region (Including Lloydminster, Hwy 16 and Key Origins)



Appendix B: Short-haul Trucking Price Index

2000-2001 Crop Year				2001-2002 Crop Year			
Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
100.0	102.5	102.5	102.5	102.5	102.5	102.5	100.0

2002-2003 Crop Year				2003-2004 Crop Year			
Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

2004-2005 Crop Year				2005-2006 Crop Year
Q1	**Q2**	**Q3**	**Q4**	**Q1**
100.0	100.0	108.8	111.3	114.7

Source: Quorum Corp. 2002

Appendix C: Full Data Set - Location Summary by Year

	% of Observations in Most Popular Origins			
Year	**Top 6**	**Top 12**	**Top 21**	**Total Observations**
2006	59.6%	69.7%	77.2%	1,549
2005	49.2%	74.1%	85.7%	2,609
2004	46.0%	57.1%	66.4%	1,202
2003	51.3%	60.6%	67.5%	1,356
2002	29.9%	40.8%	52.5%	777
2001	21.9%	34.6%	47.6%	2,566

2006	Distance (KM)	# of Observations	2005	Distance (KM)	# of Observations
Unity	164	452	Unity	164	499
Hamlin	151	134	Morinville	281	288
Dundurn	318	126	Wetaskiwin	266	143
Wetaskiwin	266	110	Allan	337	143
Allan	337	74	Hamlin	151	141
Saskatoon	277	36	North Battleford	140	73
Biggar	230	27	Biggar	230	67
Asquith	287	25	Perdue	260	61
Eston	301	24	Westlock	332	52
Ferintosh	262	24	Leask	302	47
Radisson	210	24	Prince Albert	348	47
Albertville	381	23	Quill Lake	451	43

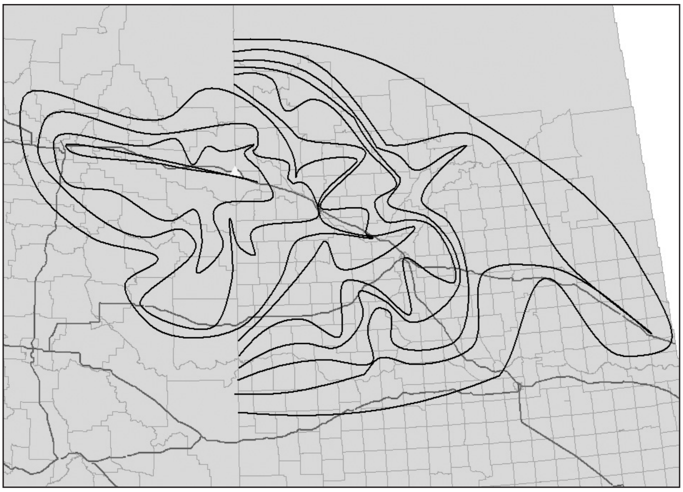
2004	Distance (KM)	# of Observations	2003	Distance (KM)	# of Observations
Unity	164	311	Unity	164	302
Prince Albert	348	72	Killam	185	152
Allan	337	55	Wetaskiwin	266	120
Wetaskiwin	266	50	Edmonton	249	42
Provost	124	37	Saskatoon	277	40
Leask	302	31	Allan	337	40
Biggar	230	28	Ferintosh	262	37
Bawlf	237	27	Provost	124	20
Borden	223	23	Sedgewick	193	20
Cutknife	119	22	Arlee	234	18
Watrous	393	20	Naicam	462	17
Bassano	463	18	Meadow Lake	189	14

2002	Distance (KM)	# of Observations	2001	Distance (KM)	# of Observations
Hamlin	151	54	Westlock	332	133
Unity	164	47	Provost	124	123
Saskatoon	277	39	Vermillion	58	82
Allan	337	31	Viking	199	80
Wetaskiwin	266	31	Saskatoon	277	79
Balcarres	607	30	Wilkie	191	66
Thorhild	271	17	Edgerton	87	60
Indian Head	602	16	Olds	462	60
Edam	145	15	Hamlin	151	58
Cutknife	119	13	Wetaskiwin	266	58
Kelvington	556	12	Milden	326	48
Sheho	537	12	Biggar	230	42

Appendix D: Selected Iso-rate Maps

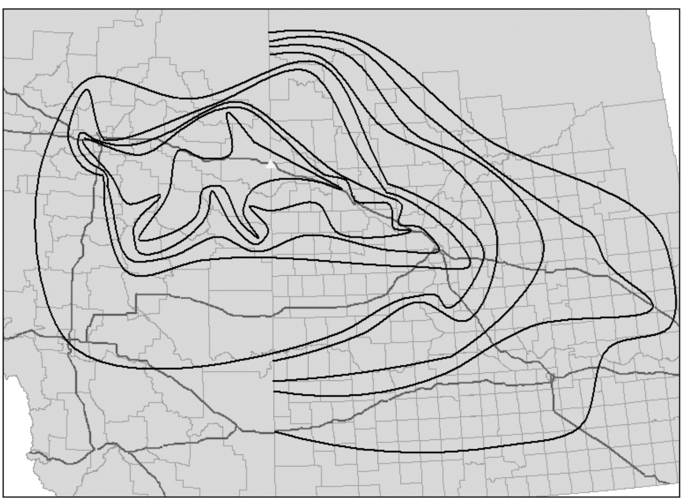
Note - North is up, scales are approximately 130-140 miles/inch, depending on the map. Lloydminster is the small white triangle located just to the left and above the center of each map. Highway 16 is the gray line passing diagonally from northern Alberta to the southeastern portion of Saskatchewan, through Lloydminster. Rate #1 is the innermost contour on each map (centered around Lloydminster), while successive rates lie outside of the prior rate. Units for the rate bounds are measured in C$ per metric tonne.

Figure 2: Spring, 2001



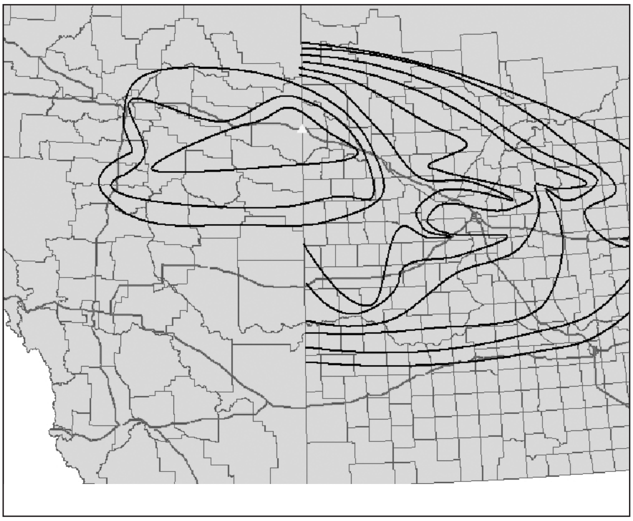
Rate	Lower Bound	Upper Bound
1	5.00	6.00
2	6.01	7.00
3	7.01	8.00
4	8.01	9.00
5	9.01	10.00
6	10.01	12.00
7	12.01	13.00
8	13.01	15.00
9	16.01	17.00
10	19.01	20.00

Figure 3: Harvest, 2001



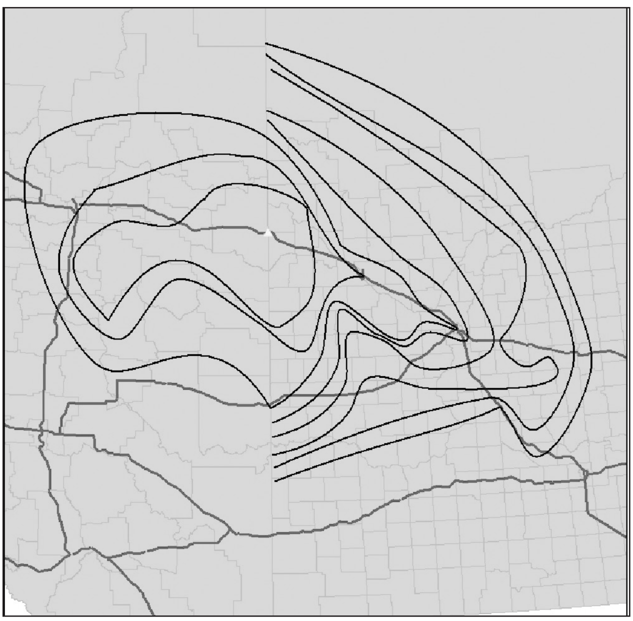
Rate	Lower Bound	Upper Bound
1	6.00	7.00
2	7.01	8.00
3	8.01	9.00
4	9.01	10.00
5	10.01	12.50
6	12.51	14.50
7	14.51	17.50
8	17.51	19.00
9	19.01	20.00
10	20.00	25.00

Figure 4: Spring, 2003



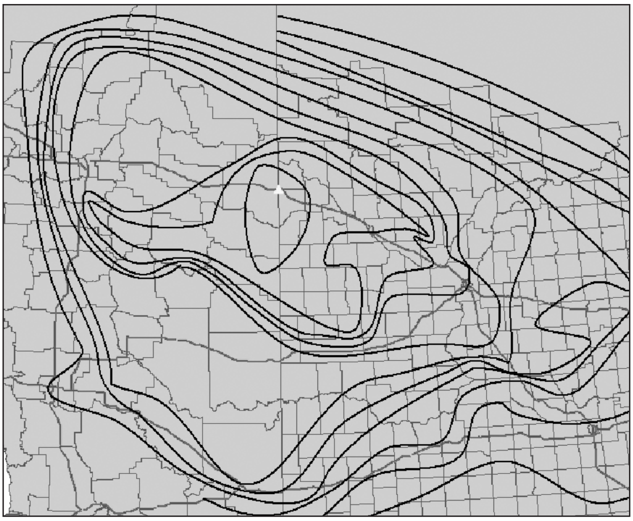
Rate	Lower Bound	Upper Bound
1	5.00	7.00
2	7.01	8.00
3	8.01	9.00
4	9.01	11.14
5	11.15	12.60
6	12.61	15.75
7	15.76	17.50
8	17.51	19.50
9	19.51	24.00

Figure 5: Spring, 2004



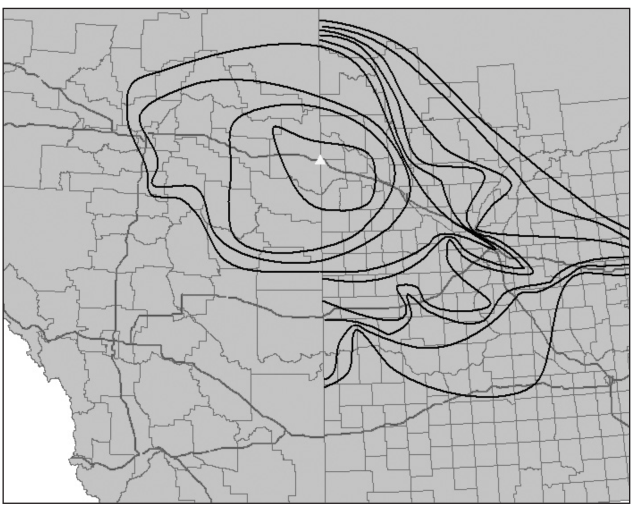
Rate	Lower Bound	Upper Bound
1	7.00	8.00
2	8.01	9.00
3	9.01	10.00
4	10.01	11.25
5	11.26	13.56
6	13.57	15.12
7	15.13	17.00
8	17.01	20.00

Figure 6: Harvest, 2004



Rate	Lower Bound	Upper Bound
1	5.00	6.00
2	9.00	10.00
3	10.01	11.00
4	11.01	12.00
5	12.01	14.00
6	14.01	17.00
7	17.01	18.00
8	18.01	19.00
9	19.01	20.00
10	20.01	21.50
11	21.51	24.00
12	26.00	30.00

Figure 7: Harvest, 2005



Rate	Lower Bound	Upper Bound
1	7.00	9.00
2	9.01	11.00
3	11.01	11.75
4	11.76	13.33
5	13.34	15.15
6	15.16	17.00
7	17.01	18.00
8	18.01	20.75
9	20.76	24.33

Appendix E: Selected Pairwise (by origin) VAR Estimates

Dependent variables are the applicable trucking rates, lagged variables as indicated. *Die* is the diesel fuel price index, *wage* is the wage rate and the seasonal dummies are labeled as such (Fall excluded). AIC diagnostics are also listed for each model. ** denotes significance at the 95% level, while * denotes significance at the 90% level, t-statistics are in square brackets.

	Model 1		Model 2	
	Weta	Big	Weta	Ham
Variables				
C	0.011416	0.027295*	0.021349	0.008001
	[0.63758]	[2.03295]	[1.15729]	[0.68378]
Weta (t-1)	-0.2818	0.302242**	-0.5469**	-0.47383**
	[-1.66711]	[2.38449]	[-2.92279]	[-3.99246]
Weta (t-2)			-0.14174	-0.5646**
			[-0.74377]	[-4.67118]
Big (t-1)	0.092033	-0.4648**		
	[0.51969]	[-3.50023]		
Big (t-2)				
Ham (t-1)			0.418152**	-0.44624**
			[2.31535]	[-3.89561]
Ham (t-2)			0.138297	-0.09932
			[0.72889]	[-0.82530]
Die	0.22505	-0.13775		
	[0.93988]	[-0.76722]		
Die (t-1)	-0.08691	-0.12629	-0.00922	0.76803**
	[-0.35486]	[-0.68768]	[-0.03336]	[4.37924]
Die (t-2)				
Wage	0.171715	-0.01756		
	[0.44190]	[-0.06027]		
Wage (t-1)	-0.21372	-0.1756	0.359127	0.424248*
	[-0.50868]	[-0.55736]	[0.95056]	[1.77045]
Wage (t-2)				
spring	-0.00134	-0.00988	-0.01131	-0.01805
	[-0.06543]	[-0.64467]	[-0.52325]	[-1.31652]
summer	-0.00058	-0.03924**	-0.01409	-0.00854
	[-0.02626]	[-2.37984]	[-0.60835]	[-0.58103]
winter	-0.02599	-0.02292	-0.02806	0.012882
	[-1.09579]	[-1.28889]	[-1.14901]	[0.83179]
AIC	-2.92118	-3.49693	-2.85007	-3.76064
AIC (model)		-6.46737		-6.71738
R-squared	0.202372	0.500266	0.331968	0.672475

	Model 3		Model 4		Model 5	
	Big	**All**	**Big**	**Ham**	**Big**	**PA**
Variables						
C	0.039343**	0.002016	0.035471*	-0.0091	0.086268**	0.052365**
	[2.18314]	[0.11592]	[1.78340]	[-0.48060]	[5.82290]	[3.15934]
Big (t-1)	-0.36673*	-0.0472	-0.49595**	-0.2198	-0.09971	0.249132
	[-2.01307]	[-0.26850]	[-3.00810]	[-1.40053]	[-0.68496]	[1.52972]
Big (t-2)					-0.34816**	0.159065
					[-2.83496]	[1.15774]
All (t-1)	0.071619	-0.38828**				
	[0.37826]	[-2.12501]				
All (t-2)						
Ham (t-1)			0.354416*	-0.25205		
			[1.97186]	[-1.47316]		
Ham (t-2)						
PA (t-1)					-0.00965	-0.77679**
					[-0.05548]	[-3.99208]
PA (t-2)					0.361588*	-0.26117
					[2.02237]	[-1.30564]
Die	-0.16224	0.178884	-0.33828*	0.046822		
	[-0.65322]	[0.74630]	[-2.02566]	[0.29454]		
Die (t-1)	-0.06198	-0.12978	0.075655	0.679063**		
	[-0.26043]	[-0.56504]	[0.44709]	[4.21574]		
Die (t-2)			-0.09813	-0.05952	0.040745	0.236305*
			[-0.49092]	[-0.31281]	[0.33935]	[1.75919]
Wage	-0.07051	-0.01674	0.323802	-0.14842		
	[-0.20401]	[-0.05018]	[0.89037]	[-0.42872]		
Wage (t-1)	0.080692	-0.72753*	0.598368	-0.45576		
	[0.21868]	[-2.04301]	[1.62842]	[-1.30299]		
Wage (t-2)			0.34819	-0.67585**	0.026342	-0.07897
			[1.09704]	[-2.23697]	[0.12818]	[-0.34347]
Spring	-0.00847	0.02628	-0.01988	-0.00174	-0.06467**	-0.05615**
	[-0.40378]	[1.29752]	[-0.92542]	[-0.08507]	[-3.59318]	[-2.78868]
Summer	-0.05927**	0.002238	-0.05777**	0.020294	-0.10597**	-0.04447**
	[-2.73876]	[0.10715]	[-2.37425]	[0.87623]	[-6.44397]	[-2.41696]
Winter	-0.03484	0.009009	-0.02225	0.018691	-0.08447**	-0.06027**
	[-1.41986]	[0.38051]	[-0.94831]	[0.83681]	[-4.50481]	[-2.87291]
AIC	-3.0395	-3.11064	-3.07504	-3.17361	-3.96743	-3.74299
AIC (model)		-6.43553		-6.2507		-7.71961
R-squared	0.477737	0.421642	0.496382	0.546429	0.805102	0.604294

	Model 6		Model 7	
	Big	**Uni**	**Ham**	**PA**
Variables				
C	0.038609	0.065098**	0.013568	0.024827*
	[1.26687]	[2.74145]	[0.64226]	[1.92250]
Big (t-1)	-0.33709	-0.09012		
	[-1.08227]	[-0.37136]		
Big (t-2)				
Uni (t-1)	-0.05293	-0.65005**		
	[-0.21308]	[-3.35855]		
Uni (t-2)				
Ham (t-1)			-0.28783	-0.25737
			[-1.03267]	[-1.51045]
Ham (t-2)				
PA (t-1)			-0.27231	-0.45814**
			[-0.93420]	[-2.57106]
PA (t-2)				
Die	-0.33664	-0.76043**	0.340703	0.076999
	[-1.07823]	[-3.12589]	[1.62820]	[0.60194]
Die (t-1)			0.118687	0.344192**
			[0.52058]	[2.46956]
Die (t-2)			0.135537	0.083268
			[0.71868]	[0.72226]
Wage	-0.10541	0.322864	0.086144	-0.26252
	[-0.21549]	[0.84705]	[0.22929]	[-1.14302]
Wage (t-1)			-0.34113	-0.10926
			[-0.82375]	[-0.43159]
Wage (t-1)			-0.18717	-0.47951**
			[-0.51181]	[-2.14483]
Spring	-0.01549	-0.05851**	-0.02148	-0.02192
	[-0.44887]	[-2.17633]	[-0.88620]	[-1.47937]
Summer	-0.04164	-0.03167	-0.01492	-0.02601*
	[-1.19567]	[-1.16702]	[-0.64273]	[-1.83307]
Winter	-0.02231	-0.06468**	-0.0089	-0.01643
	[-0.62304]	[-2.31844]	[-0.35338]	[-1.06693]
AIC	-2.82659	-3.32565	-3.10805	-4.09235
AIC (model)		-6.41407		-7.37511
R-squared	0.324896	0.605745	0.285887	0.619669

Appendix F: Pairwise Impulse Response Graphs for Each VAR Model

Note: The y-axis has no units and represents only relative magnitude of the price shock. The x-axis is in months. Relative location to Lloydminister is indicated by (**W**)est or (**E**)ast.

Fig 8: Hamlin (W)/Prince Albert (E) (Model 7)

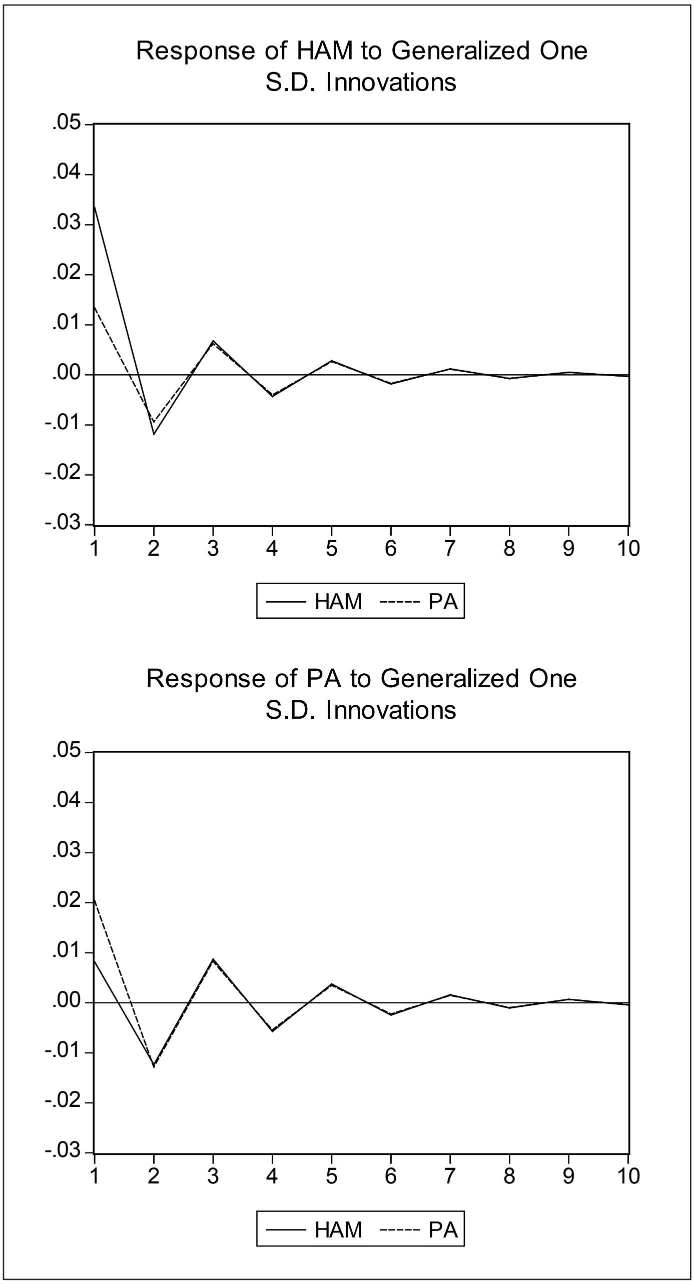


Fig 9: Wetaskiwin (W)/Hamlin(W) (Model 2)

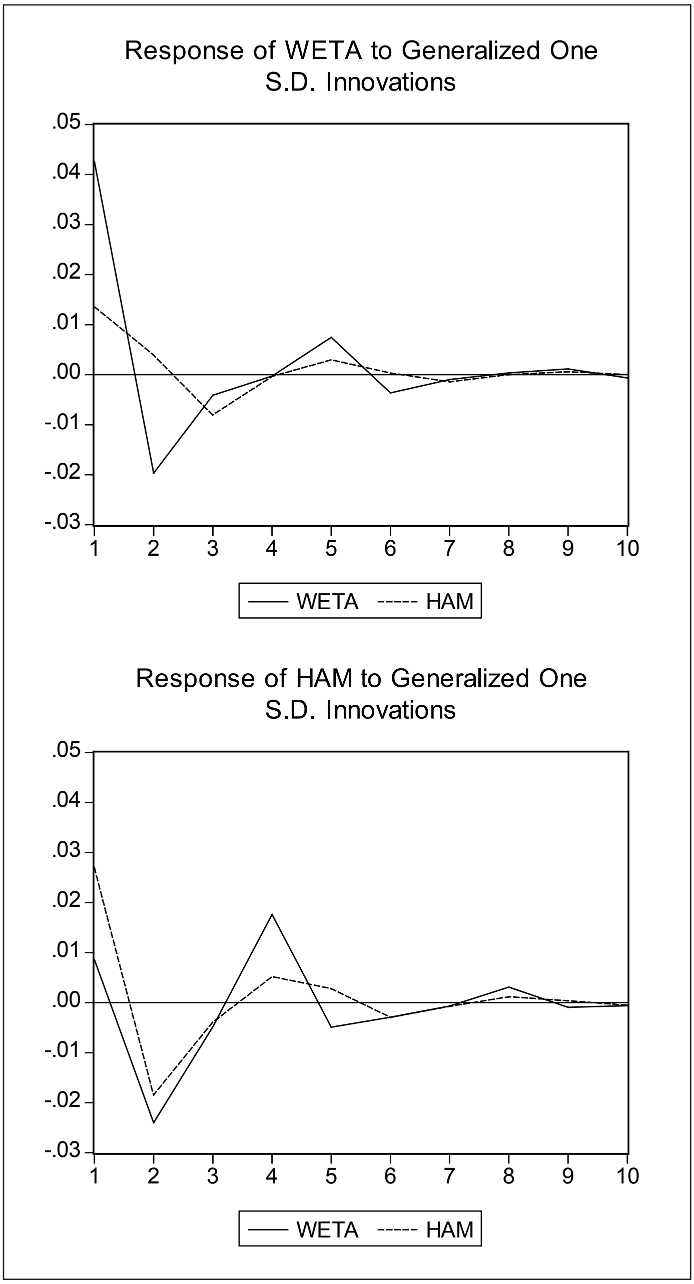


Fig 10: Wetaskiwin(W)/Biggar(E) (Model 1)

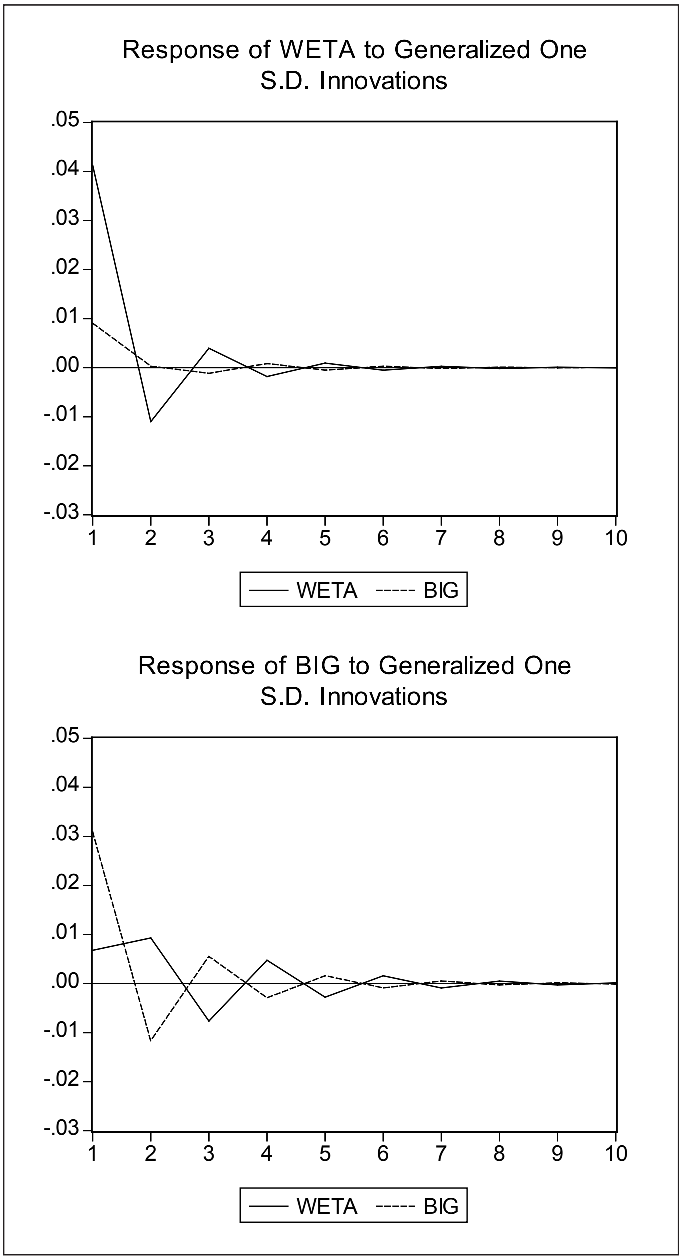


Fig 11: Biggar(E)/Hamlin(W) (Model 4)

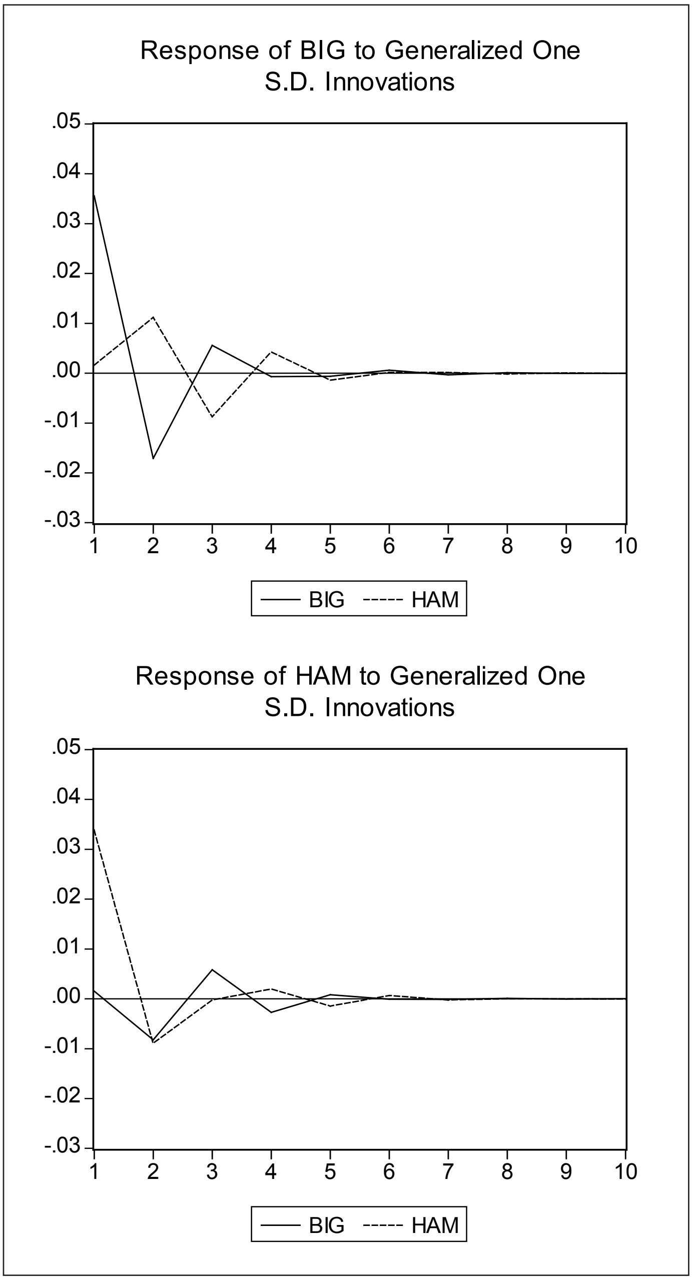


Fig 12: Biggar (E)/Allan(E) (Model 3)

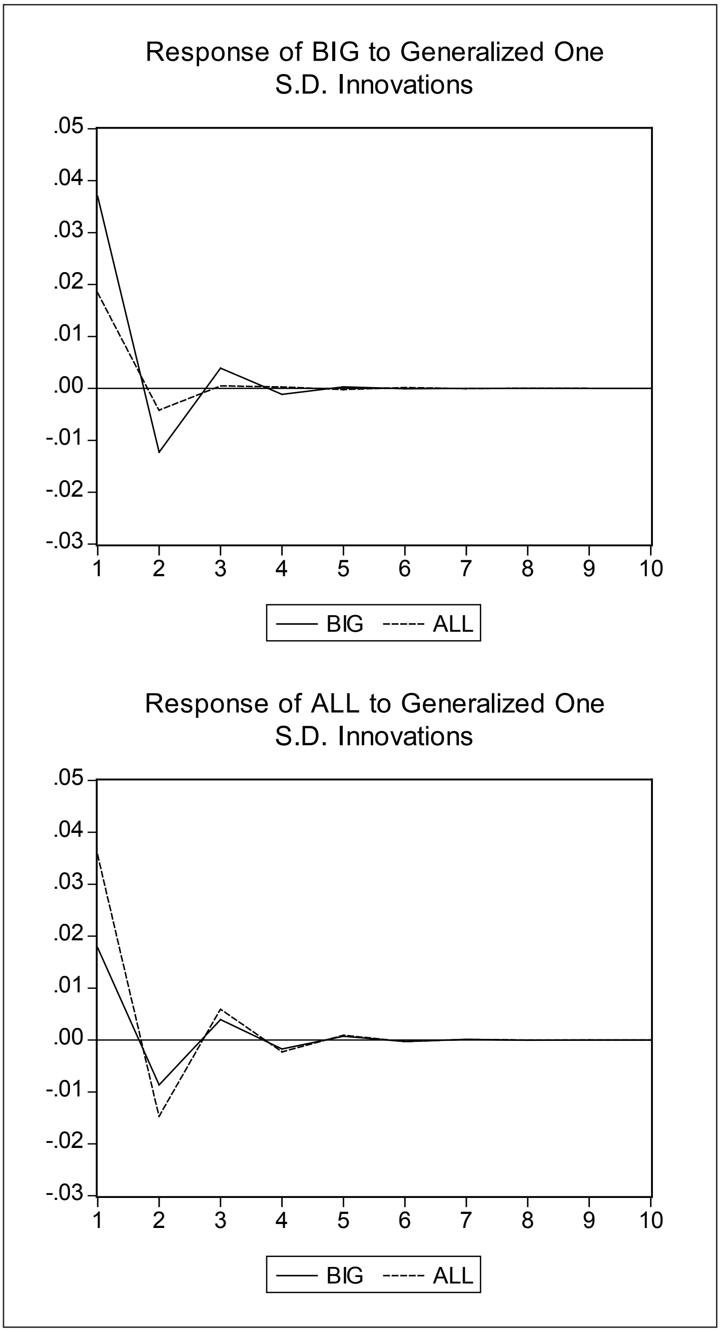


Fig 13: Biggar(E)/Prince Albert(E) (Model 5)

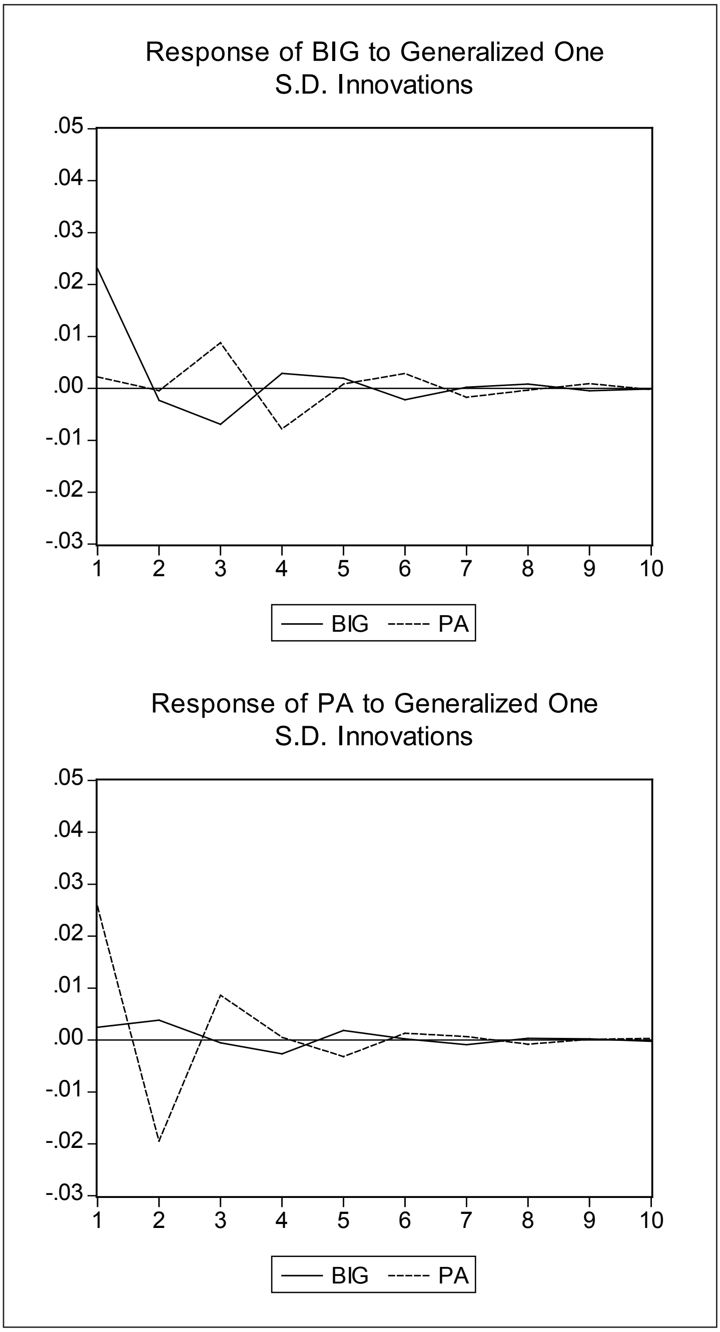
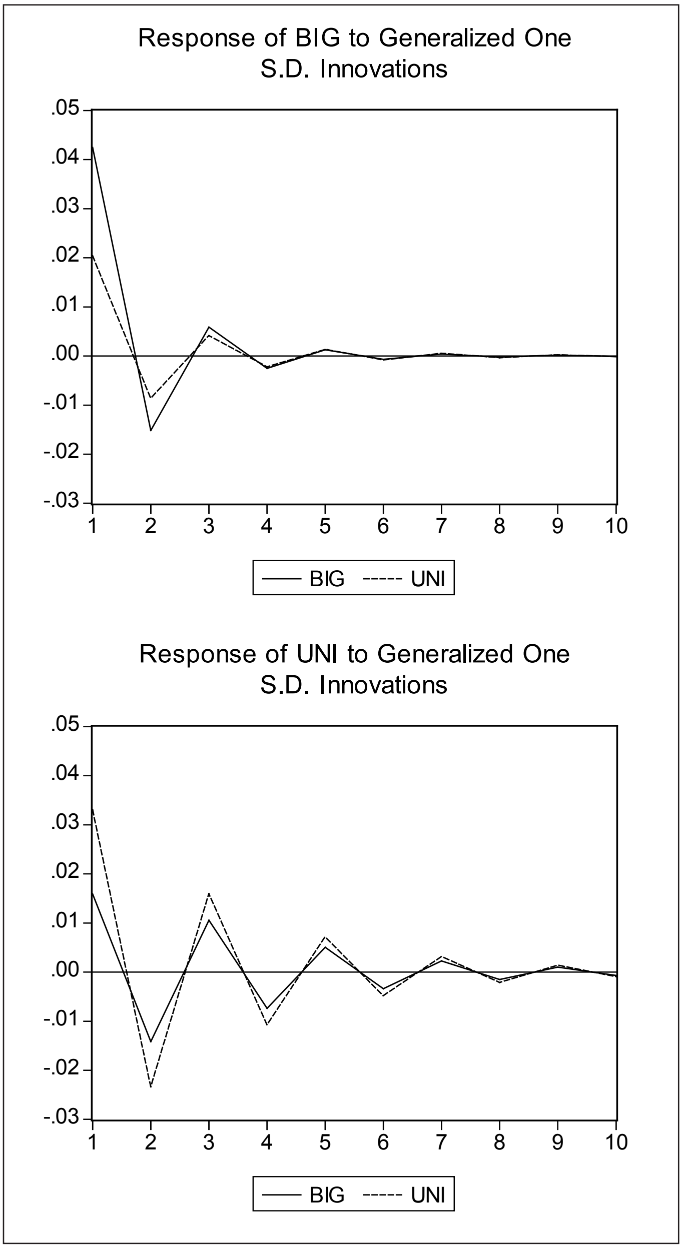


Fig 14: Biggar(E)/Unity(E) (Model 6)



Endnotes

1. The material discussed in this section was developed by the authors, motivated by the work of Newell (1980).

2. Despite considerable search efforts, we have been unable to find prior research examining rate contours in this context. Nor have we yet found or developed a suitable statistical test of "shape" for the contours (i.e., "smooth" vs. "irregular"). Work on this issue is on-going.

3. One co-author (Laing) had personal experience in the industry, indicating that this was common practice.

4. As a data mining exercise that ultimately generates trucking rate impulse responses in order to assess market power and market integration, our brief discussion about the estimated VAR coefficients is offered merely for exposition. By comparison, DeVany and Walls (1996, 1999) did not discuss properties of their VAR coefficient estimates, although they were listed in each paper. Finally we note that each of the specified VAR models converged with either one or two variable lags, while the reported Akaike Information Criterion (AIC) was used to assess relative model stability (Murray 2006).

5. Kim and McMillin (2003) observed that a large number of insignificant coefficients are often generated from this type of analysis.

6. As alluded to in a previous footnote, one of the co-authors of the paper (Laing) was directly involved in this process while the data were collected.

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Modeling Frequency of Truck Crashes on Limited-Access Highways

by Niranga Amarasingha and Sunanda Dissanayake

Freight can be efficiently transported between most locations in the U.S. using large trucks. Involvement of large trucks in crashes can cause much damage and serious injuries, due to their large sizes and heavy weights. The purpose of this study was to identify the relationships between large truck crashes and traffic and geometric characteristics on limited access highways. Crash and traffic and geometric-related data for Kansas were utilized to develop a Poisson regression model and a negative binomial regression model for understanding the relationships. Based on model-fitting statistics, the negative binomial model was found to be the better model, which was used to identify the important characteristics. By addressing identified factors, safety could be promoted through introduction of appropriate engineering improvements.

INTRODUCTION

In the United States, large trucks provide a convenient mode for the movement of freight from origin to destination. The American Trucking Association reported a 47% increase in registered large trucks and a 65% increase in their miles traveled from 1988 to 2008 (ATA 2012). In 2009, large trucks accounted for 4% of all registered vehicles and 10% of total vehicle miles traveled in the U.S. (NHTSA 2009). Trucks with gross vehicle weight greater than 10,000 pounds are typically considered large trucks, and 296,000 of such trucks were involved in traffic crashes on U.S. roadways during 2009 (NHTSA 2009). There were 3,380 fatalities and 74,000 injuries reported due to those large truck crashes that year. Also, according to 2009 statistics, large trucks represented about 7% of vehicles in fatal crashes, 2% of vehicles in injury crashes, and 3% of vehicles in property-damage-only crashes (NHTSA 2009). Involvement of large trucks in crashes can cause much damage and serious injuries due to their large sizes and heavy weights. In 2009, occupants of large trucks comprised only 22% of fatalities resulting from fatal large truck crashes, while 78% of the fatalities occurred outside the truck to pedestrians, cyclists, and, primarily, occupants of passenger vehicles (NHTSA 2009).

Injuries and severity of injuries that occur in a crash increase exponentially with vehicle speed (Stuster 1999). However, long distance freight transportation requires large trucks to have access to interstate and state highways and operate at higher speeds. Also, drivers may face vehicle control challenges or difficulties while driving large trucks on interstate or state highways at high speeds. Interstates and urban highways serve a diverse combination of passenger vehicle traffic, local delivery truck traffic, and long-haul truck traffic.

Analysis of large truck crash data indicates there are traffic and highway geometric characteristics associated with large truck crashes (Miaou 1994). Highway geometric design features such as a horizontal curvature, vertical grade, lane width, lane type, shoulder width, shoulder type, and median are engineering factors which might be used to reduce the number of large truck crashes. One of many important aspects of highway safety research is developing crash prediction models to quantify the relationship between traffic and geometric characteristics and the number of crashes observed. Identifying the effects of traffic and geometric characteristics is important to promote safety by introducing engineering improvements. The focus of this research was to understand and evaluate the effects of both traffic conditions and site characteristics on the occurrence of large truck crashes.

LITERATURE REVIEW

Several previous studies have investigated the relationship between crash rates and traffic and geometric design features. A number of crash frequency models have been developed for large truck crashes exclusively. Mohamedshah et al. (1993) investigated traffic and geometric-related variables that affect truck crashes using data from the Highway Safety Information System (HSIS). Multivariate logistic models for truck crashes on interstates and two-lane rural roads were developed considering truck crash data in Utah from 1980 to 1989. As indicated by the statistically significant variables in the interstate model, truck crashes were primarily affected by horizontal curvature and vertical gradient. Vertical gradient is inclination of road surface to the horizontal plane while horizontal curvature can be defined as a measure of the sharpness of a horizontal curve. When values of horizontal curvature or vertical grade increases, the number of truck crashes increases. For two-lane rural roads, as indicated by the statistically significant variables in the model, truck crashes were affected by shoulder width and horizontal curvature. With the increase of the horizontal curvature, the number of truck crashes increases; however, shoulder width and number of truck crashes have a negative relationship.

Miaou (1994) evaluated the relationship between truck crashes and geometric design features of road sections using Poisson regression, Zero-Inflated Poisson regression, and negative binomial regression models. Data were obtained from the HSIS, which included 1,643 large truck crashes occurring on Utah highway sections within the five-year period from 1985 to 1989. Estimated regression parameters from all three models were quite consistent in terms of estimated relative frequencies of truck crashes across road sections. The developed models were then evaluated based on estimated regression parameters, overall goodness-of-fit, predicted relative frequency of truck crashes, sensitivity to the inclusion of short road sections, and estimated total number of truck crashes. Evaluation results showed that Poisson regression models were best to use as the initial model for developing the relationship, while other forms of models could be explored if the over-dispersion (i.e., the variance of crash frequency in the dataset exceeds the mean of the crash frequency) of crash data is found in the Poisson model. According to estimated coefficients of the significant variables, truck crashes increase with the increase of the annual average daily traffic (AADT) per lane, horizontal curvature, and vertical grade while number of truck crashes decrease with the increase of percentage of trucks in the traffic.

Schneider et al. (2009) developed a negative binomial regression model using crash data from Ohio to investigate the effect of rural two-lane horizontal curves on truck crashes at non-intersection locations. Data were obtained from the Ohio Department of Public Safety and Ohio Department of Transportation's roadway inventory files, which includes all heavy-duty truck crashes related to single- and multi-vehicle crashes on horizontal curves. This study further investigated implementation of Bayesian methods on model performance. Impact of shoulder width, curve radius, curve length, and traffic parameters on truck crashes were considered in the model development. The significant variables in the final model were length of horizontal curve, truck annual daily traffic (ADT), passenger ADT, and degree of horizontal curve. Each of these variables had a positive relationship with the number of truck crashes. The developed model was used to target improvements to specific roadways. The model could also be used to identify truck crashes that may occur in the future due to volume increases. The authors pointed out the need for improved models to accommodate other, non-volume-related contributing factors to truck crashes to improve the truck-crash-frequency prediction.

Virginia crash data were used by Joshua and Garber (1990) to find the quantitative relationship between traffic and geometric variables, and the probability of occurrence of large truck crashes.

Geometric data such as number of lanes, lane and shoulder widths, and vertical and horizontal alignments were collected directly from the sites at which a large number of truck-related crashes occurred. Multiple linear and Poisson regression analyses were carried out in order to predict the number of truck crashes, where the Poisson regression model was found to be capable of better describing the relationship. It indicated that the rate of change of slope (change in vertical grade divided by the length of the highway segment), average daily traffic, percent of trucks, and speed differential between trucks and non-trucks had significantly influenced the number of truck crashes. Increase of each of these variables indicated more truck crashes.

Daniel et al. (2002) developed a crash prediction model for truck crashes on route sections with signalized intersections. Crash data were obtained from New Jersey accident records, and volume and geometric data were obtained by reviewing straight-line diagrams and contract drawings of the roadway. A Poisson regression model and a negative binomial regression model were developed. Coefficients of the negative binomial model were comparable with those for the Poisson regression model with some exceptions. Coefficients of both models showed significant impact based on segment length, AADT, length of vertical grade, number of lanes, number of signals within the segment, and pavement width on truck crash frequency on selected roadways. According to both models, with the increase of segment length, AADT, number of lanes, and number of signals within the segment, the number of truck crashes increase. The increase in the length of vertical grade and pavement width showed decreased number of truck crashes.

DATA

Crash data from 2005 to 2010 were obtained from the Kansas Department of Transportation (KDOT), which were utilized for analysis in this study. These data, included in the Kansas Accident Reporting System (KARS) database, comprise all police-reported crashes in Kansas. For this study, large truck crash records on limited-access highways were extracted by making the query from all crashes from 2005–2010 for the state of Kansas. From 2005 to 2010, 5,392 large trucks were involved in crashes on limited-access highways. After identifying these large truck crashes, information to locate each crash on the highway was obtained from the Control Section Analysis System (CANSYS) database.

The CANSYS database, maintained by KDOT, is a highway inventory system that includes many traffic- and geometric-related details of national and state highways in Kansas. Data from 2005 to 2010 were obtained for limited-access highways, and sections were defined based on homogeneity of road segments and data availability. The selected sections were homogenous in terms of number of lanes, horizontal curvature, median width, AADT, truck AADT percent, lane width, shoulder width, and existence of rumble strips. Additionally, variables such as functional class, section length, and year were considered in the analysis. For this study, data on vertical grade (i.e., inclination of road surface to the horizontal plane) were provided by KDOT from construction drawings, as vertical grades are not frequently updated in the CANSYS database.

A total of 16,853 roadway segments were initially identified where the length varied from 0.10 miles to 19.87 miles, with an average segment length of 0.81 miles. Data were reviewed and sections which had speed limits lower than 55 mph and lengths shorter than 0.25 miles were discarded. A total of 7,273 roadway segments were considered for further analysis. Table 1 shows summary characteristics of road segments used in the analysis. All roadway sections were divided-roadway sections, as the focus of this study is on limited-access roads.

Table 1: Traffic- and Geometric-Related Characteristics of Limited-Access Highway Sections

Variable	Description	Sections No.	Sections %	Variable	Description	Sections No.	Sections %
Section Length (SL, in miles)	$0.25 \leq SL < 0.50$	2,466	33.91	*Right Rumble Strips*	Yes	4,492	61.76
	$0.50 \leq SL < 1.00$	2,053	28.23		No	2,781	38.24
	$1.00 \leq SL < 2.00$	1,302	17.90	*Inside Rumble Strips*	Yes	4,200	57.75
	$2.00 \leq SL < 3.00$	522	7.18		No	3,073	42.25
	$3.00 \leq SL < 4.00$	265	3.64	*Right Shoulder Width (ft)*	0	68	0.93
	$4.00 \leq SL$	665	9.14		2	24	0.33
Speed Limit (mph)	55	122	1.68		6	46	0.63
	60	769	10.57		8	195	2.68
	65	1,486	20.43		9	8	0.11
	70	4,896	67.32		10	6,838	94.02
Median Width (MW, in ft)	$MW<10$	92	1.26		12	94	1.29
	$10 \leq MW < 20$	2,087	28.70	*Inside Shoulder Width (ft)*	0	2,845	39.12
	$20 \leq MW < 30$	349	4.80		2	41	0.56
	$30 \leq MW < 40$	3,997	54.96		3	8	0.11
	$40 \leq MW$	748	10.28		4	32	0.44
Functional Class	Expressways	1,211	16.65		6	2,970	40.84
	Rural interstate	3,351	46.07		7	16	0.22
	Urban interstate	2,711	37.27		8	126	1.73
AADT per lane (veh/day/lane)	Less than 1,000	302	4.15		9	511	7.03
	1,000 - 2,000	2,965	40.77		10	696	9.57
	2,000 - 3,000	1,224	16.83		12	28	0.38
	3,000 - 4,000	629	8.65	*Horizontal Curve*	Curve	660	9.07
	4,000 - 5,000	437	6.01		Straight	6,613	90.93
	More than 5,000	1,716	23.59	*Vertical Grade*	Level	6,795	93.43
AADT of Large Truck Count (veh/day)	Less than 1,000	1,549	21.30		Grade	478	6.57
	1,000 - 2,000	4,728	65.01	*Number of Lanes*	4	5,855	80.50
	2,000 - 3,000	768	10.56		6	1,220	16.77
	More than 3,000	228	3.13		8	198	2.72

Shoulder widths and rumble strips were recorded separately for inside (or left) and outside (or right) lanes in a given direction. Absolute values of horizontal curvature and vertical grade on each homogeneous section were used for the modeling. Sections having either positive or negative horizontal curvature or vertical grade are more dangerous for trucks than other sections where the roadway is level and straight. For example, since trucks may not be able to maintain normal, prevailing traffic speeds on steep upgrades, they may lead to sudden braking by the following vehicles, resulting in overturning or rear-end crashes. Total number of crashes occurring within each segment was determined by combining crash data and CANSYS data. About 35% of the road segments had at least one large truck crash, regardless of truck configurations and crash-severity type, while the remaining segments did not have any reported large truck crashes during the years that were being considered. Large crashes are potentially affected by human factors as well, but data related to human factors were unavailable or not possible to be aggregated based on individual road sections. Similar situation exists for contributory causes for each section as well. The omitted and unavailable factors were kept consistent to better understand the effect of traffic and geometric relationships that are being investigated.

METHODOLOGIES

Various statistical models could be considered for identifying relationships between number of large truck crashes and geometric and traffic characteristics. Because of the random and discrete nature of crashes, Poisson regression has long been considered as a good starting point for frequency modeling (Miaou 1994).

Poisson Regression Model

Poisson regression model is appropriate for dependent variables that have non-negative integer values such as 0, 1, 2… Hence, in most cases, count data could be precisely analyzed by Poisson regression (Pedan 2001). More details of Poisson regression analysis can be found in Long (1997).

The Poisson regression model was proposed by Miaou (1994) to find the relationship between vehicle crashes and geometric design features of road sections, such as lane width, shoulder width, horizontal curvature, and lane width. The Poisson regression model proposed by Miaou (1994) is given by:

$$(1)\quad P(Y_i = y_i) = p(y_i) = \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!}, \quad (i = 1,2,3,\ldots n;\; y_i = 0,1,2,3,\ldots)$$

where,

- i = a roadway segment. The same roadway segments in different sample periods are considered as separate roadway segments.
- y_i = the number of large truck crashes for a year for roadway segment i.
- $P(y_i)$ = probability of the occurrence of y_i large truck crashes for a year on roadway segment i.
- μ_i = mean value of large truck crashes occurring for a year as:

$$(2)\quad \mu_i = E(Y_i) = \vartheta_i[e^{\sum_{j=1}^{k} x_{ij}\beta_j}]$$

where,

- x_{ij} = the j^{th} independent variable for roadway segment i,
- β_j = the coefficient for the j^{th} independent variable, and
- ϑ_i = traffic exposure for roadway segment i.

Associated with each roadway segment i, x_i independent variables describe geometric characteristics, traffic conditions, and other relevant attributes. Traffic exposure, which is the amount of large truck travel during the sample year, can be computed as:

$$(3)\quad \vartheta_i = 365 \times AADT_i \times T\%_i \times l_i$$

where,

- ϑ_i = traffic exposure on segment i,
- $AADT_i$ = Annual Average Daily Traffic (vehicles/day),
- $T\%_i$ = percentage of large trucks in traffic stream, and
- l_i = length of the road segment.

This model assumes the number of large truck crashes for a given time period for roadway segments (Y_i; i = 1,2, ... n) are independent of each other and Poisson distributed with mean. The expected number of large truck crashes $E(Y_i)$ is proportional to large truck travel ϑ_i. The model ensures that the crash frequency is positive, using an exponential function given by:

$$(4)\quad \lambda_i = \frac{E(Y_i)}{\vartheta_i} = \exp\left(x_i' \beta\right)$$

where,

λ_i = exposure-based number of large truck crashes,
$E(Y_i)$ = expected number of large truck crashes,
x_i' = transpose of covariate vector x_i , and
β = vector of unknown regression parameters.

One important property of Poisson regression is that it restricts the mean and variance of the distribution to be equal. This can be written as:

$$(5)\quad \mathrm{Var}(y_i) = E(y_i) = \mu_i$$

where,

μ_i = mean of the response variable y_i ,
$E(y_i)$ = expected number of response variable y_i , and
$\mathrm{Var}(y_i)$ = variance of response variable y_i .

If this equality does not hold, the data are said to be either underdispersed or overdispersed, and the resulting parameter estimates will be biased. If the overdispersion is not captured in the analysis, the standard errors are underestimated and, hence, it becomes an overstatement of significance in hypothesis testing (Pedan 2001). If the model fits the data, both deviance and Pearson Chi-Square statistics divided by the degrees of freedom are approximately equal to one. The deviance is the likelihood-ratio statistic for comparing the model to the saturated model, which explains all the variation in the data. Values greater than one indicate the variance is an overdispersion, while values smaller than one indicate an underdispersion. It is possible to account for overdispersion with respect to the Poisson model by introducing a scale (dispersion) parameter into the relationship between the variance and the mean (Pedan 2001).

Another way to address overdispersion, if it exists, is the consideration of a distribution that permits more flexible modeling of the variance. The negative binomial regression model is more appropriate for overdispersed data because it relaxes the constraints of equal mean and variance.

Negative Binomial Regression Model

The following details of negative binomial regression models related to highway large truck crashes were described in many studies (Miaou 1994, Schneider et al. 2009, and Daniel et al. 2002). Consider a set of n highway sections of a limited-access highway. Let Y_i be a random variable representing the number of large trucks involved in crashes on highway section i during the analysis period. Further, assume the amount of large truck travel or large truck exposure on this highway section, V_i , is also a random variable estimated through a highway sampling system. Associated with each highway section i is a $k \times 1$ vector of explanatory variables, denoted by $\underline{x}_i = (x_{i1} = 1, x_{i2}, \ldots \ldots x_{ik})'$, describing its geometric characteristics, traffic conditions, and other relevant attributes. Given V_i , and x_i , large truck crash involvements Y_i, i = 1,2,3, ..., n, are postulated to be independent, and each is Poisson distributed as follows (Miaou 1994):

(6) $$P(Y_i = y_i) = \frac{(\lambda_i \vartheta_i)^{y_i} e^{-\lambda_i \vartheta_i}}{y_i!}$$

where,

λ_i = large truck crash involvement and

ϑ_i= exp (random error).

If a loglinear rate function is used as follows, the model becomes the negative binomial regression model that gives the relationship between the expected number of crashes occurring at the i^{th} section with K number of parameters.

(7) $$\lambda_i = \exp(\beta_0 X_{i0} + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{iK} + \varepsilon_i)$$

where,

λ_i = number of large truck crashes on limited-access highway section i, with negative binomial distribution conditional on ε_i,

β_0 = constant term,

$\beta_1, \dots \dots, \beta_n$ = estimated parameters in vector form,

$X_1, \dots \dots, X_n$ = explanatory variables in vector form, and

$\in_i$ = random error; exp(($\in_i$) is distributed as gamma with mean 1 and variance α^2.

In the case of the Poisson regression model, coefficients β_i are estimated by maximizing the log likelihood $\log_e L(\beta)$.

Assessment of the Models

In order to assess the adequacy of models, the basic descriptive statistics for the event count data first need to be investigated (Pedan 2001). The models developed using the relevant statistically significant variables are further tested for goodness-of-fit, which includes deviance statistics and Pearson Chi-Square statistics.

Deviance statistics are used to assess the fit of the model and overdispersion. These statistics are sometimes referred to as the likelihood ratio statistics or G-squared value. The G-squared value is the sum of deviance, and is defined as the change in deviance between the fitted model and the model with a constant term and no covariates. The G-squared statistics are given by (Agresti 2007):

(8) $$G^2 = 2\Sigma_{=1}^{n} y_i \ln(y_i / E(y_i))$$

where,

G^2 = deviance,

y_i = observed number of large truck crashes,

E(y_i) = expected number of large truck crashes, and

n = number of road sections.

If this statistic is significant, then the covariates contribute significantly to the model. If not, other covariates and/or other error distributions need to be considered. Deviance is approximately a chi-squared random variable with degrees of freedom (DF) equal to the number of observations (n) minus the number of parameters (p). A value of the deviance over ($n – p$) that is degrees of freedom, suggests the model is overdispersed due to missing variables and/or a non-Poisson form. Thus, when deviance divided by degrees of freedom is significantly larger than one, overdispersion is indicated.

Pearson Chi-Squared statistics are used to assess the presence of overdispersion in the model and are given in equation (9) (Agresti 2007):

$$(9)\quad x^2 = \Sigma_{i=1}^{n} \frac{(y_i - \lambda_i)^2}{\lambda_i}$$

where,

y_i = observed number of large truck crashes
λ_i = expected number of large truck crashes, and
n = number of road sections.

If value of the Chi-Squared statistics over degrees of freedom is larger than 1, overdispersion is also indicated. If Pearson Chi-Square statistics divided by degrees of freedom and deviance statistics divided by degrees of freedom are both closer to one, it indicates a better model fit.

ANALYSIS RESULTS

With consideration given to variables used in the literature and data availability, candidate variables were selected and the definitions of variables considered for individual road sections, along with the descriptive statistics, are presented in Table 2. A total of 17 explanatory variables were selected to be considered in the model. The existence of right rumble strip and inside (left) rumble strip were considered as categorical variables. As the number of lanes varies from section to section, AADT per lane was considered in the modeling. Maximum horizontal curvature was 4% per 100 ft of arc (degrees of curvature), while the maximum grade was 3.35%. There was considerable variation of risk across the years due to long-term trends, and changes in omitted variables such as road surface conditions and weather. Therefore, year-to-year changes in overall large truck crashes were captured using yearly dummy variables in the model.

Poisson Regression Model

A Poisson regression model was developed, taking into account the previously explained variables. Goodness-of-fit statistics showed that deviance/DF and Pearson Chi-Square statistic/DF were both slightly higher than 1.00, which suggested more variability among counts than would be expected for Poisson distribution. The descriptive data also indicated the overdispersion of data showed the mean number of crashes in a section was 0.66 with a variance of 1.34, as given in Table 2.

One of the most common reasons for data being overdispersed is that μ_i parameters vary not only with measured covariates, but with latent and uncontrolled factors. Hence, without any adjustment for overdispersion, the Poisson model was not quite adequate to describe the occurrence of large truck crashes on limited-access highways in Kansas. Accordingly, the Poisson model was adjusted for overdispersion by including a scale (dispersion) parameter, as presented in Table 3. The scale parameter was estimated by considering a ratio of the Pearson Chi-Square to its associated degrees of freedom. The estimated scale parameter was 1.2145 and scaled Pearson Chi-Square was fixed to one.

In Table 3, the coefficient of each independent variable influencing the large truck crashes in the model gave the size of the exponential effect of a particular variable on the number of large truck crashes. The coefficients of continuous variables bearing a positive sign indicated an increase in large truck crashes with an increase of the variable, while a negative sign indicated a decrease in large truck crashes with an increase of the variable. The coefficient of dummy or indicator variables bearing a positive sign indicates the dummy or indicator variable switch from 0 to 1; that is an increase of crashes. A unit change in the variable would affect large truck crashes by an exponential power of that variable coefficient, if all other variables were kept constant. The variables that were

Table 2: Variable Definitions for Limited-Access Highway Large Truck Frequency Modeling

Variable	Description	Notation and Definition	Min	Max	Mean	Std. Dev.
TRUCK_NUM	Number of large truck crashes in a section	y_i	0	32	0.66	1.34
SEC_LEN	Section length (miles)	l_i	0.25	19.87	1.51	2.20
TR_EXPO	Truck miles or truck exposure (log scale)	$\vartheta_i = (365 \times AADT_i \times T\%_i \times l_i) / 1000$	6.10	14.04	10.63	1.12
Y_2005	Dummy variable for year 2005	x_{i1} = 1, if road section is in year 2005; 0 otherwise	0	1	0.15	0.35
Y_2006	Dummy variable for year 2006	x_{i2} = 1, if road section is in year 2006; 0 otherwise	0	1	0.15	0.36
Y_2007	Dummy variable for year 2007	x_{i3} = 1, if road section is in year 2007; 0 otherwise	0	1	0.15	0.36
Y_2008	Dummy variable for year 2008	x_{i4} = 1, if road section is in year 2008; 0 otherwise	0	1	0.16	0.36
Y_2009	Dummy variable for year 2009	x_{i5} = 1, if road section is in year 2009; 0 otherwise	0	1	0.18	0.38
Y_2010	Dummy variable for year 2010	x_{i6} = 1, if road section is in year 2010;0 otherwise	0	1	0.21	0.40
AADT	Surrogate variable to indicate traffic conditions or traffic density	$x_{i7} = (AADT_i / no.\ of\ lanes_i) / 1000$	0.15	13.83	3.35	2.48
HC	Horizontal curvature (absolute value in degrees per 100ft arc)	x_{i8}	0	4	0.11	0.43
VG	Vertical grade (absolute value in percent)	x_{i10}	0	3.35	0.23	0.58
IN_SHOULD	Inside shoulder width	x_{i12}	0	12	9.83	1.17
R_SHOULD	Right-side shoulder width	x_{i13}	0	12	6.99	1.88
TRUCK	Percent large trucks in the traffic stream (log scale)	x_{i14}	1.42	39.16	10.63	1.12
IN_RUMBLE	Dummy variable for inside rumble strip	x_{i5} = 1, if inside rumble strip exists; 0 otherwise	0	1	0.61	0.48
R_RUMBLE	Dummy variable for right rumble strip	x_{i5} = 1, if right rumble strip exists; 0 otherwise	0	1	0.57	0.49
SPEED	Speed limit (mph)	x_{i16}	55	70	67.67	3.75
L_WIDTH	Lane width (ft)	x_{i17}	12	20	12.06	0.53
NUM_LANE	Number of lanes	x_{i18}	2	8	4.21	0.78
MD_SHOULD	Median width (ft)	x_{i19}	0	60	23.51	29.21

significant at 95% confidence interval were section length, number of lanes, lane width, horizontal curvature, vertical grade, AADT per lane, inside shoulder width, inside rumble strip, and yearly dummy variables for 2005, 2006, 2007, and 2008.

Negative Binomial Regression Model

The negative binomial regression model naturally accounts for the overdispersion, as its variance is greater than the variance of a Poisson distribution. Hence, the model developed in the previous section was reinvestigated using negative binomial assumptions. The maximum likelihood estimates of negative binomial regression model parameters, including the dispersion parameter and goodness-of-fit statistics, are given in Table 3. Both significant and insignificant variables were presented in the table because the primary objective in developing models is to understand the effect of each variable. The sign of the significant variables did not change after removing the insignificant variables from the model.

The dispersion parameter of the estimated negative binomial regression model was 0.5596. Since the dispersion parameter was greater than zero, the response variable was overdispersed. If the deviance value was equal to zero, the model was considered to be a perfect-fit model. Thus, the lowest deviance value was considered to have a better fit. Pearson Chi-Square statistics divided by degree of freedom, and deviance statistics divided by degree of freedom closer to one, indicated a better model fit. Scaled deviance statistics divided by degree of freedom (0.804) were closer to one in the developed negative binomial regression than that of the Poisson regression model (0.771). Hence, the negative binomial model was selected as the better model that can be used to identify the relationship between number of large truck crashes and traffic and geometric-related characteristics on limited access roadways.

Each significant variable in the negative binomial model affected the number of large truck crashes and the magnitude of the coefficient gave the size of the exponential effect of that variable on the number of large truck crashes. The coefficients of continuous variables bearing a plus sign indicate an increase in large truck crashes due to the variable, while a minus sign indicates a decrease in large truck crashes with an increase in the variable. Coefficient of dummy or indicator variables bearing a positive sign indicated that when the dummy or indicator variable switches from 0 to 1 there is an increase in number of crashes. The significant variables in the negative binomial model were section length, number of lanes, horizontal curvature, vertical grade, AADT per lane, large truck percent, inside shoulder width, and annual dummy variables, 2005-2008. The effect on the number of large truck crashes from each of these variables is explained below.

Length of Section: The negative binomial model showed that section length has a positive sign, signifying that for a unit increase in length of a section, crash frequency also increases if all other variables are kept constant. The effect of section length on expected crash frequency showed that shorter sections were less likely to have more large truck crashes than longer sections. This finding was expected and compatible with previous findings on the relationship between length of section and large truck crash frequencies (Miaou 1994, Schneider et al. 2009, Joshua et al. 1990).

Number of Lanes: The variable for number of lanes was significant with a positive coefficient. This means that as the number of lanes increases, opportunities for conflicts related to lane changes also increases, thereby increasing the number of crashes. This was also found by previous researchers (Miaou 1994).

Horizontal Curvature: The horizontal curvature-related variable indicated large truck crashes were less likely on sharp curves. This finding was rather difficult to explain, even though it is compatible with some of the previous findings (Daniel et al. 2002, Milton and Mannering 1998). The variable,

Table 3: Developed Poisson Regression Model and Negative Binomial Model

Variable	Description	Poisson Regression Model		Negative Binomial Model	
		Estimate	P-value	Estimate	P-value
Intercept		-14.260	<0.001	-3.775	<0.001
SEC_LEN	Section length (in mile)	0.1738*	<0.001	0.2231*	<0.001
L_WIDTH	Lane width (in ft)	0.1363*	0.010	0.0491	0.348
SPEED	Posted speed limit (in mph)	-0.0068	0.302	0.0067	0.331
NUM_LANE	Number of lanes	0.0927*	<0.001	0.0652*	0.013
HC	Horizontal curvature (in degree per 100ft arc)	-0.6097*	<0.001	-0.5622*	<0.001
VG	Vertical grade	-0.4348*	<0.001	-0.3916*	<0.001
AADT	AADT of the traffic stream per lane	0.1592*	<0.001	0.2035*	<0.001
TRUCK	Large Truck Percent**	-	-	0.0141	<0.001
R_SHOULD	Right shoulder width in ft	0.0360	0.217	0.0069	0.802
IN_SHOULD	Inside shoulder width in ft	0.0697*	<0.001	0.0863*	<0.001
Y_2005	Dummy variable for year 2005	0.3706*	<0.001	0.3691*	<0.001
Y_2006	Dummy variable for year 2006	0.2289*	<0.001	0.2266*	0.002
Y_2007	Dummy variable for year 2007	0.1915*	0.001	0.2629*	<0.001
Y_2008	Dummy variable for year 2008	0.1546*	0.002	0.2110*	0.001
Y_2009	Dummy variable for year 2009	-0.1209	0.071	-0.0984	0.1404
MD_SHOULD	Median width in ft	-0.0017	0.217	-0.0005	0.698
R_RUMBLE	Dummy variable for right rumble strip	0.0501	0.470	-0.0590	0.447
IN_RUMBLE	Dummy variable for inside rumble strip	-0.2532*	0.001	-0.1071	0.215
Scale		1.2145		-	
Dispersion		-		0.5596	
Goodness-of-Fit Statistics					
Criterion		Value	Value/DF	Value	Value/DF
Deviance		8,256	1.138	5,897	0.813
Pearson Chi-Square		10,701	1.475	7,338	1.011
Scaled Deviance		5,597	0.771	5,830	0.804
Scaled Pearson Chi-Square		7,255	1.000	7,255	1.000
Number of Observations (road sections)		7,273		7,273	

Note: * *Significant values at 95% confidence level*
** *Large truck percent in Poisson regression model was considered as an exposure variable*

horizontal curvature, works in conjunction with the length of the section; hence, the net effect of a horizontal curvature on large truck crash frequencies seems to be inconclusive, as some of the past studies found a positive relationship between large truck crash frequencies and horizontal curvature (Miaou 1994, Mohamedshah et al. 1993, Schneider et al 2009), while others did not.

Vertical Grade: Vertical grade was negatively correlated with large truck crash frequency. One possible explanation was that curves in vertical plane on a limited-access highway consist of minor initial grades and adequate sight distances. The combination of upgrades and downgrades may not be giving a clear relationship between the vertical grades and large truck crash frequencies. However, many previous studies have used the absolute value of vertical grade as an independent variable when modeling the crash frequencies (Miaou 1994, Mohamedshah 1993, Joshua and Garber 1990). The negative relationship between truck crashes and vertical grade was also found by Daniel et al. (2002) when investigating intersection-related crashes.

AADT per Lane: An increase in AADT per lane tended to increase large truck crash frequency. As the number of vehicles through a section increases, exposure to potential crash situations and number of conflicts also increases. This finding was expected, and a relationship was also found in previous studies by Miaou (1994) and Mohamedshan et al. (1993).

Large Truck Percent: Positive coefficient of the large truck percent in the model indicated that as the percentage of large trucks through a section increases, the number of crashes increases. This is consistent with the expectation that the number of truck crashes should increase if there are proportionally more large trucks. Some of the previous research has found that large truck crash frequency decreases with an increase in the percentage of large trucks (Miaou 1994, Milton and Mannering 1998). The explanation in those studies was that the presence of more large trucks reduced vehicle overtaking and lane changing behaviors, which are more crucial for safety. However, if and when the AADT is relatively low, even a few additional trucks on roadways increase the truck percentage (Milton and Mannering 1998). Thus, large truck crashes may decrease in some cases when AADT is low, because of lack of conflicts, not because of an increase in large trucks. Another study has shown that the number of large truck crashes increases with an increase in large truck AADT (Schneider et al. 2009). Hence, large truck percentage works in conjunction with the AADT, making large truck percentage to be another inconclusive variable.

Inside Shoulder Width: Inside shoulder width had a positive correlation with the number of large truck crashes, meaning the number of crashes increases when inside shoulder width increases. A similar relationship has been found by Ivan et al. (1999) when analyzing two-lane rural highways. However, with narrower shoulder widths, drivers have less room to take corrective actions after making an errant maneuver, and drivers are more likely to be involved in fixed-object crashes with the reduced widths. Hence, it was expected to see a decreased number of large truck crashes when shoulder width was increased. So the result was not expected.

Yearly Dummy Variables: The coefficient of yearly variables for 2005, 2006, 2007, and 2008, which represented unmeasured factors, was positive and significant. This means the overall number of large truck crashes increased due to unmeasured factors not included in the model. Similar findings were documented by Miaou (1994).

In this study, absolute values for the variables' vertical grade and horizontal curvature were used because the considered analysis unit includes both directions of travel. A positive gradient value for one direction is a negative for the other direction. One possible way to address this issue is to model the crashes on one direction of travel at a time; however, many previous research studies modeled crashes on both directions considering the absolute values of horizontal curvature (Miaou 1994, Joshua and Garber 1990, Schneider et al. 2009). The reason that the variable on horizontal curvature was inconclusive may also be due to segmentation issues; however, modeling without considering horizontal curves sections did not affect the results on how other variables are affecting the outcome either. Variables such as speed limit, shoulder width, and road width have certain fixed values for each road segment. Hence, these can be defined either as categorical or dummy variables, which might have had some effect on the outcome. Some of the results such as horizontal curvature, vertical grade, and inside shoulder width, from the Poisson regression model and negative binomial model were not as expected. Hence, advanced model formats such as random parameter negative binomial model or Zero-Inflated models may be tested in the next steps, to check whether that might lead to a more robust model.

Based on the developed model, the relationship between large truck crashes and geometric design features, traffic, and other characteristics were identified. The identified effective parameters in large truck crashes can be considered as the criteria for improving highway safety. According to the developed models, it can be concluded that the variables such as number of lanes, AADT, and large truck percent have a specific impact on large truck crashes. Developed models can be used to identify target improvements to limited-access highways to reduce large truck crashes. Also, these can be used to form public policy and highway design criteria. This understanding offers important insight into the relationship between safety and mobility that will improve the quality of decisions made by practicing engineers and planners.

DISCUSSION

In roadway designing, features normally considered are road cross-section elements such as roadway median, utility and landscape areas, drainage channels and side slopes; sight-distance considerations; and horizontal/vertical curvatures as per the design guides. One of the most important factors in design of a limited-access highway facility is design speed. For urban areas, the designer needs to select a reasonable design speed, considering access restrictions and type of access control that can be achieved. Limited-access roadways need to be designed with smooth-flowing horizontal and vertical alignments. Proper combination of horizontal curvature, grades, and median types are expected to provide safety and aesthetics of roadways. The dimensions, weight per axle, and operating characteristics of a vehicle influence design aspects such as width of the lane and curvature. Additionally, consideration of human, traffic, and environmental factors are important in designing roadways as well (Bonneson and Lord 2005).

In recent years, a number of studies have been conducted on geometric design features, safety and operational effect of those designs, and how they influence other activities. The National Cooperative Highway Research Program has reported those findings in Synthesis Report 432 (Brewer 2012). According to the report, large trucks are given important consideration in the geometric design. Some research has given several recommendations for updating existing design guides. Lamm et al. (2002) have developed a process to evaluate the safety of horizontal alignment on two-lane rural roads. This methodology allows designers to predict potential crash risks and safety-related concerns of an alignment, and make changes or develop countermeasures. The occurrence of crashes on two-lane highways is different than on multilane divided highways, but a similar process for evaluating the safety of horizontal alignment on multilane highways may be developed.

Engineers and transportation planners make decisions to add travel lanes on a freeway when they find the capacity of the road needs to increase. According to results of this study, the number of large truck crashes increases when the traffic volume increases. Engineers and planners may believe that decreased traffic is associated with some degree of improved safety. However, results also showed that crashes increase with an increase in the number of lanes. Hence, the introduction of barrier-separated lanes, express lanes, and managed lanes such as toll roadways and dual-dual lanes are effective strategies to offset the increase of conflict opportunities associated with an increase in the number of lanes (Kononov et al. 2008). Dual-dual lanes are managed lanes that have physically separated inner and outer lanes in each direction. The inner lane is reserved for light vehicles, while the outer roadway is open to all vehicles. These lane strategies are a treatment for a specific section of roadway that has a unique set of characteristics such as vertical grades, weaving area, and high percentage of large truck traffic.

The percent increase of large truck traffic is increasing the number of large truck crashes. This is an important matter for all drivers because it affects speed of travel, safety, comfort, and convenience. Hence, many transportation agencies have implemented a variety of countermeasures for large trucks in an attempt to mitigate the effects of increasing large truck traffic. One such example is exclusive truck lanes (Kuhn et al. 2005). California operates an exclusive truck roadway on IH-5 in the Los Angeles area. While other vehicles are allowed to use the roadway, trucks are the primary users. This limited-access road section that includes vertical grades allows slower truck speeds than the free-flow speed of other vehicles, especially in the uphill direction. The Managed Lanes Handbook suggests exclusive barrier-separated truck lanes if truck volumes exceed 30% of the vehicle mix, peak-hour volumes exceed 1,800 vehicles per lane-hour, and off-peak volumes exceed 1,200 vehicles per lane-hour (Kuhn et al. 2005).

The focus of this study was limited to the investigation of the relationship between roadway geometric characteristics and large truck crashes. However, countermeasures for improving safety are not only limited for geometric improvements but also improvements in pavement markings, traffic signs, roadside improvements, lighting, and changing regulations. According to results, the percent increase of truck traffic is increasing the number of truck crashes. To mitigate the effects of increasing truck traffic, exclusive truck lanes can be used. However, just by increasing number of lanes, fewer truck crashes cannot be expected as results showed a positive relationship between number of lanes and truck crash frequency. Table 4 shows a general countermeasure list that could be used to improve the safety of roadways focusing on all possible areas (Washington et al. 2002). For example, if the case of sharper horizontal curves cannot be avoided, countermeasures such as warning signs can be used to provide enough guidance to the driver. Widening and improving clear zones is an alternative countermeasure, which also helps to reduce run-off-road crashes. This may include flattening side slopes, removal of roadside obstacles, and increasing available stopping distance adjacent to the road. As identified in this study, geometric changes such as horizontal alignments decrease large truck crash frequency. Geometric alternations may be considered when other less costly countermeasures are not effective and when the current roadway geometry designs can significantly benefit from improvements. Before implementing countermeasures, the most effective countermeasures and specific conditions for which they are effective need to be identified. The countermeasures related to road geometry and traffic conditions discussed in this paper are related to preventing large truck crashes, but preventing or reducing the number of truck crashes overall improves traffic safety as well. Not all countermeasures can be implemented simultaneously. Also, some countermeasures are less effective when introduced in isolation.

SUMMARY AND CONCLUSIONS

Traffic- and geometric-related data and crash data for limited-access roads were utilized in this study to model or predict large truck crash frequency in Kansas. Data yielded 7,273 homogeneous, limited-access roadway segments which had speed limits of more than 55 mph and lengths of more than 0.25 miles. Poisson and negative binomial regression models were used to estimate the effects of independent variables. According to the coefficients of the developed negative binomial models, large truck crash frequency increased when the length of a section, the number of lanes, AADT per lane, and inside shoulder width increased. Vertical grades were significantly negatively correlated with large truck crash frequency. Also, the overall number of large truck crashes increased due to unmeasured factors that were not in the model.

The results of the negative binomial model may be used for improvement to limited access highways and to prevent or mitigate large truck crashes. Large trucks need to be given important consideration in the geometric design. Revision of existing design guides needs to take into account current dimensions of large trucks and vertical curvature considerations. A process for evaluating the safety of horizontal alignment on multilane highways can be an effective countermeasure. This process allows designers to predict potential crash risks and safety-related concerns of an alignment, and make changes or develop countermeasures. Introduction of exclusive truck lanes,

Table 4: A General Countermeasure List for Improving Roadway Safety

Category	Countermeasure	
Pavement Markings	Add/Upgrade Edgeline	
	Add Raised Pavement Markings (RPMs)	
Traffic Signs	Warning Signs	
	Advisory Speed Signs	
	Chevron Alignment Sign: These Advance Warning Traffic Signs are used to warn drivers of existing or potentially hazardous condition ahead.	
	Post Delineator: These are designed to aid motorists in identifying the alignment of the roadway when utilized in roadside or centerline	
Roadway Improvements	Modify Geometric Alignment	
	Improve Sight Distance without Geometric Realignment	
	Add Turn Lanes/ Barrier-Separated Lanes/Managed Lanes	
	Improve Longitudinal Shoulder	Add/Widen Graded/Stabilized Shoulder
		Pave Existing Graded Shoulder of Suitable Width
		Widen and Pave Existing Paved Shoulder
	Add Rumble Strips	
Roadside Improvements	Install/Upgrade Guardrail	
	Upgrade Guardrail End Treatment/ Add impact Attenuator: These are usually placed in front of fixed structures to reduce the damage to structures, vehicles, and motorists resulting from a motor vehicle crash.	
	Clear Zone Improvements	Widen Clear Zone
		Flatten Side Slope
		Relocate Fixed Object
		Remove Fixed Object
		Convert Object to Breakaway
		Construct Traversable Drainage Structure: Cross-drainage structures with openings (which are used to move water under the roadway) within the clear zone should be made traversable
Lighting	Add Segment Lighting	
	Add Intersection Lighting	
Regulations	Enforcement Speed Limits	

Source: Washington et al. (2002)

barrier-separated lanes, express lanes, and managed lanes such as dual-dual lanes and toll roadways are effective strategies to offset the increase of conflict opportunities associated with an increase in the number of lanes. Warning signs on approaching curves and widening and improving clear zones are countermeasures for decreasing large truck crash involvement. This research provides a step to identifying traffic- and geometric-related factors that contribute to large truck crashes.

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Transportation Research Forum

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