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On the cover: An overlooked area of transportation is the structure of grain shipping on the Great Lakes and St. Lawrence Seaway system. This omission is remedied by the article authored by Pizzey and Nolan titled "Pass the Salt: Markets for Grain Shipping on the Great Lakes." (cover photo: *Editorial credit:/Shutterstock.com*)

A Message from the JTRF Co-General Editors

The Summer 2017 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:

- Illicit drug use and motor vehicle fatalities
- Kansas safety performance functions for rural multilane segments and intersections
- Indian vehicle ownership determinants
- Market structure of grain shipping on the Great Lakes
- Application of decision tree models to examine motor vehicle crash severity outcomes
- Stochastic modeling of the last mile problem for delivery fleet planning

In "Analysis of Illicit Drug Use and Motor Vehicle Fatalities," Andrew Welki and Thomas Zlatoper analyze the influence of illicit drug use on highway fatalities using regression models using data for 48 states for the years 2009 and 2010. They found significant life-taking effects from marijuana use for the very youngest drivers. Comparable effects from the usage of cocaine and non-medical pain relievers occur among older drivers. They also found that real per-capita income and seat belt use were negatively related to the highway death rate. The following variables are positively related to the death rate: the ratio of rural to urban driving, temperature, speed limit, the percentage of older drivers, and cell phone use.

Syeda Aziz and Sunanda Dissanyake adjust existing safety performance functions (SPFs) for Kansas conditions in "Calibration of Highway Safety Manual Given Safety Performance. Functions for Rural Mainline Segments and Intersections in Kansas." The authors note that predictive methods in the Highway Safety Manual (HSM) are of limited use if they are not calibrated for local conditions. Calibration procedures given in the HSM were followed for rural segments and intersections. They found that the HSM overpredicts fatal and injury crashes and underpredicts total crashes on rural multilane roadway segments. The authors examined a way to adjust HSM calibration procedures by development of new regression coefficients for existing HSM-given SPF. They also found that final calibration factors obtained through modified SPFs indicated significant improvement in crash prediction for rural multilane segments.

In "Indian Vehicle Ownership: Insights from Literature Review, Expert Interviews, and State Level Model," Prateek Bansal and Kara Kockelman review existing vehicle ownership models for India and describe results of nine experts' interviews to gather insights about Indian travel patterns and vehicle choices. The authors found that vehicle price, fuel economy, and brand are the most decisive factors in car choices according to the experts. They also found that states with a higher proportion of computer-owning households and higher share of households living in rural areas with larger household size are likely to have higher car ownership.

Logan Pizzey and James Nolan assess the structure of grain shipping within the Great Lakes and St. Lawrence Seaway system in "Pass the Salt: Markets for Grain Shipping on the Great Lakes." The authors hypothesize that if the salt market in the Great Lakes St. Lawrence System (GLSLS) is competitive, the data should indicate that rates originating in the Great Lakes are cointegrated with rates for grain originating in the Lower St. Lawrence. In order to investigate whether or not the sets of rates are cointegrated, the authors conduct a basic Engle-Granger test for cointegration on the seaway rate data. However, the authors were unable to conclude that grain shipping rates within the two seemingly linked transportation markers were cointegrated.

In "An Application of Decision Tree Models to Examine Motor Vehicle Crash Severity Outcomes," Jill Bernard Bracy estimates and compares classification regression tree (CART) and chi-square Automatic Interaction Detection (CHAID) models. Using Missouri crash data from 2002-2012, the author examines the impact of several variables on crashes. These include driver characteristics and behaviors, temporal factors, weather conditions, and road characteristics. The author found that the CHAID model was significantly better than the CART model in terms of

ability to discriminate amongst severity outcomes. Also, results suggest that the presence of alcohol, speeding, and failing to yield lead to many fatalities each year and likely have interactive effects. Decision rules are used to identify changes in driving policies expected to reduce severity outcomes.

Jay R. Brown and Alfred L. Guiffrida present a stochastic representation of the last mile problem in "Stochastic Modeling of the Last Mile Problem for Delivery Fleet Planning." The authors quantify expected maintenance, regular labor, overtime labor, fuel, and carbon emissions resulting from different delivery fleet options. The authors say their model can be used in a decision framework to evaluate alternative delivery strategies involving fleet size and delivery frequency as well as the transportation capacity needed to meet customer demand. The authors say their model advances the literature in this area by creating a decision framework that includes a distribution of expected travel distance, probabilistic service levels, a carbon emissions component, and a multiple vehicle fleet of varying size.

Michael W. Babcock
Co-General Editor-JTRF

James Nolan
Co-General Editor-JTRF

An Analysis of Illicit Drug Use and Motor Vehicle Fatalities Using Contiguous State-Level Data

by Andrew M. Welki and Thomas J. Zlatoper

This paper analyzes the influence of illicit drug use on highway fatal outcomes by estimating regression models using data for the 48 contiguous U.S. states for the years 2009 and 2010. The models include a representative, but not exhaustive, collection of roadway fatality determinants. The impact of illicit drug usage on the motor vehicle death rate differs across age groups. There are statistically significant life-taking effects from marijuana use by the very youngest drivers. Comparable effects from the usage of cocaine and nonmedical pain relievers occur among older drivers. Negatively associated with the highway death rate and statistically significant are real per capita income and seat belt use. Statistically significant positive relationships with the rate are found for the ratio of rural to urban driving, temperature, speed limit, the percentage of older drivers, and cell phone usage. The paper provides information to policy makers at a time when state-level drug laws are changing rapidly. Evidence reported here on how drug use affects highway fatal outcomes is relevant to that discussion.

INTRODUCTION

Driving under the influence of psychoactive (mind-altering) drugs is unsafe, placing at risk both motor vehicle occupants and others using highways (National Institute on Drug Abuse 2014). In 2009, one third of fatally injured U.S. drivers tested positive for drugs other than alcohol (National Highway Traffic Safety Administration [NHTSA] 2010a). This suggests there is a serious drugged driving problem nationally. Despite that reality, the U.S. lags other countries in research and enforcement related to this issue (DuPont 2011).

This paper investigates the influence of illicit drug use on U.S. highway safety. Specifically, it estimates the relationship between such usage and motor vehicle fatalities, while controlling for the impact of a representative collection of highway death determinants. A unique contribution is the utilization of state-level data, including information on drug use broken down by drug types and user age groups.

This study has the following format: The first section summarizes research findings for the U.S. on drug use by drivers and the impact of such usage on highway crash risk. A model that explains motor vehicle fatalities is specified in the second section. The paper's third section describes the data set used in the analysis, with regression estimates of the model reported and discussed in the fourth section. The final section summarizes the paper's findings.

DRUGGED DRIVING IN U.S.

The 2007 National Roadside Survey (NRS) provided the first estimates of drug-involved driving for the U.S. (Lacey et al. 2009). The data collection involved randomly stopping drivers at 300 locations, primarily at night on Fridays and Saturdays but also during the daytime on Fridays. Breath, oral fluid, and blood specimens were collected and tested for alcohol as well as three broad categories of drugs: illegal, prescription, and over-the-counter. Using a similar data collection methodology, the 2013-2014 NRS was the second U.S. survey that measured drug-involved driving (Kelly-Baker et al. 2016).

Berning, Compton and Wochinger (2015) reported the following findings from the 2007 NRS and the 2013-2014 NRS on drug use by U.S. drivers: In 2013-2014, the extent of usage of any illegal drug was lower during weekday daytime (12.1%) than during weekend nighttime (15.2%); but usage of only medications (prescriptions and over-the counter) was higher during weekday daytime (10.3%) than during weekend nighttime (7.3%). During weekend nighttime, prevalence of any illegal drug increased from 12.4% in 2007 to 15.1% in 2013-2014, and prevalence of only medications grew from 3.9% in 2007 to 4.9% in 2013-2014. THC (delta 9 tetrahydrocannabinol), the psychoactive substance in marijuana, was the drug with the greatest growth in weekend nighttime prevalence—from 8.6% in 2007 to 12.6% in 2013-2014.

Utilizing data from both the 2007 NRS and the Fatality Analysis Reporting System (FARS), Li, Brady, and Chen (2013) conducted a case-control study of driver drug use and fatal crash risk, including the impact of a drug-alcohol interaction. Their findings indicated that driver fatal crash risk increases (in ascending order) with the use of marijuana, narcotics, stimulants, and depressants. Additionally, results suggested that combining drugs and alcohol especially heightens the risk.

From persons hospitalized in California between 1990 and 2005, Callaghan and others (2013) constructed groups consisting of patients diagnosed with the following drug use disorders: methamphetamine, alcohol, opioids, cannabis, cocaine, or multiple drugs. Following the cohorts for several years, the researchers calculated standardized mortality rates (adjusted for age, sex, and race) for motor vehicle accident (MVA) deaths to compare to the general population of California. For every cohort, the standardized fatality ratios were elevated, implying higher MVA death risk for individuals with drug use disorders. Standardized ratios were similar for females and males.

Like Li, Brady, and Chen (2013), Romano and others (2014) used data from both the 2007 NRS and FARS to conduct a case-control analysis of fatal crash risk. They estimated logistic regressions that accounted for five predictors—gender, age, race/ethnicity, alcohol use, and drug use. Drug usage was found to increase the likelihood of fatal injury for both sober and drinking drivers. However, when drug use was divided into marijuana and other drugs, only the latter had a significant impact on fatal crash risk. Interaction between drugs and alcohol was not found to affect the risk.

Rudisill and others (2014) conducted a trend analysis using FARS data to identify changes in drug use patterns among drivers killed in U.S. motor vehicle crashes. Using a random effects model, they calculated prevalence rates and prevalence ratios comparing the patterns in 2009−2010 to those in 1999−2000. Their results indicated that usage of prescription drugs (e.g., narcotics and depressants) in general and cannabinoids has grown, while cocaine use apparently has diminished. The authors concluded that drug use among fatally injured drivers has increased and that a shift may have occurred, changing from illegal to prescription drugs.

Lacey and others (2016) conducted a case-control analysis of the influence on crash risk of driver use of drugs and alcohol. They utilized crash data from Virginia Beach, Virginia, over a 20-month period ending in 2012. Unlike the aforementioned case-control studies (Li, Brady, and Chen 2013; Romano et al. 2014) that focused on fatal crashes, Lacey and others (2016) considered fatal, injury, and property-damage crashes, although most in the data set were property-damage only. When not adjusting for other factors, marijuana use was found to increase crash risk; but after statistically controlling for age, gender, race/ethnicity, and alcohol use, neither marijuana nor any of the other over-the-counter, prescription and illegal drugs considered increased risk. Findings indicated that, adjusting for other factors, alcohol use increased crash risk, and there was no interactive effect between alcohol and drugs.

MODEL

The model used here explicitly includes five categories of explanatory factors: economic conditions, locational factors, weather conditions, regulations, and driver characteristics.[1] Its general form is the following:

(1) DEATHRT = f(INCOME, RURURB, TEMP, PRECIP, SPEEDLIM, YOUNG, OLD, SBELTUSE, CELLPHN, ALCOHOL, DRUGUSE)

where DEATHRT = motor vehicle death rate;
INCOME = consumer income;
RURURB = rural-urban driving mix;
TEMP = temperature;
PRECIP = precipitation;
SPEEDLIM = speed limit;
YOUNG = young drivers;
OLD = old drivers;
SBELTUSE = seat belt use;
CELLPHN = cell phone use while driving;
ALCOHOL = alcoholic intoxication while driving;
DRUGUSE = drug use while driving.

An explanation of the expected relationship between each explanatory factor and the death rate is below.

Income captures the prevailing economic conditions. Its impact on highway fatalities is uncertain a priori. Higher income should increase the demand for safety and driving intensity, assuming both are normal goods.[2] Peltzman (1975) conjectures that the direction of the relationship between income and deaths is unclear due to these offsetting considerations. Loeb, Talley, and Zlatoper (1994, pp. 18-19) report that time-series studies provide evidence that supports a positive relationship, while cross-sectional and pooled analyses indicate a negative association.

Travel speeds are generally higher during rural, as opposed to urban, driving; and emergency medical treatment is typically more available in urban settings. As a result, the chance of death is likely greater when an accident occurs in a rural location. Loeb, Talley, and Zlatoper (1994, pp. 32) cite time-series and cross-sectional studies providing statistically significant evidence of inverse associations between motor vehicle fatality measures and the proportion of total travel occurring on urban highways. Given these findings, the locational measure employed here—the ratio of rural to urban travel—is anticipated to be positively related to the death rate.

The prevailing weather affects driving conditions. Loeb, Talley, and Zlatoper (1994, p. 34) report, based on cross-sectional analyses, that temperature and precipitation have statistically significant positive and negative associations, respectively, with highway fatality measures. Consistent with these results, the same associations are expected in this study.

This analysis controls for one driving regulation, the speed limit. Loeb, Talley, and Zlatoper (1994, p. 67) cite statistically significant findings, from time-series studies, that the speed limit is directly related to U.S. highway fatality rates and state-level driver injury rates. A similar positive relationship is hypothesized in this analysis.

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

Another driver characteristic addressed is seat belt use. According to NHTSA (2001, Exhibit 6) estimates, the manual lap-shoulder belt is highly effective in saving the lives of car drivers. The

National Center for Statistics and Analysis (2015) calculates that seat belt usage in passenger vehicles saved almost 13,000 lives in 2014. In contrast, Garbacz (1990) finds that seat belt use has no statistically significant effect on total, or driver, or overall occupant deaths. Further, it has a life-taking impact on non-occupants and passengers. Given this mixed evidence, the expected relationship between highway fatality rates and seat belt use is uncertain a priori.

Drivers' use of cell phones is controlled for in this study. Cell phone usage can be life-taking when it distracts drivers, leading to fatal accidents. Alternatively, it can save lives by increasing the likelihood of quick assistance when an accident occurs. Using U.S. time-series data, Loeb, Clarke, and Anderson (2009) estimate highway fatality models that allow for a nonlinear cell phone effect. They find statistically significant evidence that the impact of mobile phones is nonmonotonic and depends on the volume of phone usage. As the volume increases, the effect is first net life-taking, then net life-saving, and lastly life-taking. Given the high volume of cell usage during the analysis period, cell phones are hypothesized to have a net life-taking influence on highways.

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

Drug use is the driver characteristic of particular interest in this study. As reported earlier, Li, Brady, and Chen (2013) find that fatal crash risk increases with such usage across a variety of drugs. The same relationship is expected here.

DATA

Annual data for the 48 contiguous U.S. states in the years 2009 and 2010 are utilized in this study. The dependent variable DEATHRT is measured using highway deaths per billion vehicle-miles. The source for the death and vehicle-miles figures is the Federal Highway Administration (FHWA) (various years).

The independent variable INCOME (real per capita disposable income, in dollars) is based on total nominal disposable income values from the Bureau of Economic Analysis (2011), population figures from the U.S. Census Bureau (2011 and 2014), and values of the Consumer Price Index for all urban consumers (base period: 1982-84) [Bureau of Labor Statistics (2014)]. FHWA (various years) is the data source for the explanatory variable RURURB (rural vehicle-miles divided by urban vehicle-miles). Weather variable information−TEMP (annual mean temperature, in degrees Fahrenheit) and PRECIP (annual precipitation, in inches)−comes from the National Climate Data Center (2011). The Ohio Insurance Institute (2015) supplies the information for SPEEDLIM (maximum rural interstate speed, in miles per hour) for the 48 states.

FHWA (various years) is the data source for the age-related driver characteristics, YOUNG (percentage of licensed drivers aged 24 years or younger) and OLD (percentage of licensed drivers aged 65 years or older). Information on SBELTUSE (seat belt use rate) for 2009 and 2010 comes from NHTSA (2010b) and NHTSA (2011), respectively. Figures used to calculate CELLPHN (per capita mobile telephone subscriptions) are from the Federal Communications Commission (2013) and the U.S. Census Bureau (2011 and 2014).[3] Values for ALCOHOL (per capita apparent alcohol consumption, in gallons) for 2009 come from the National Institute on Alcohol Abuse and Alcoholism (NIAAA) (2011) and for 2010 come from NIAAA (2014).[4]

Data to capture drug use while driving come from the Substance Abuse and Mental Health Services Administration (2012).[5] This information is provided for all ages combined (age group 12+) as well as for the following age subgroups (12−17, 18−25, and 26 and over) For all ages combined, three alternate sets of measures approximate drug usage in this study[6]: (1) IDRUSPMO12+ (illicit drug use in the past month, percentage of age group 12+)[7]; (2) MARIJPMO12+ (marijuana use in the past month, percentage of age group 12+), and IDROMPMO12+ (illicit drug use other

than marijuana in the past month, percentage of age group 12+)[8]; (3) MARIJPYR12+ (marijuana use in the past year, percentage of age group 12+), COCAIPYR12+ (cocaine use in the past year, percentage of age group 12+), and NMPRPYR12+ (nonmedical use of pain relievers in the past year, percentage of age group 12+). These three alternate sets of drug use measures are also broken down by the age subgroups. For example, IDRUSPMO1217 is illicit drug use in the past month as a percentage of the 12−17 age group. Table 1 provides summary statistics on all the variables used in the model estimations.

ESTIMATION RESULTS

The variables below ALCOHOL in Table 1 identify some patterns, across age categories, of drug usage. Across the three drug categories (marijuana, cocaine, and nonmedical use of pain relievers), the highest reported use is in the 18-25 age group. Alternatively, the group 26 years or older identifies with the lowest use, except for cocaine, for which its reported use rate (1.414%) is slightly higher than that of the 12-17 age group (1.029%). Further, usage rates for marijuana are higher in the last year than in the last month. Additionally, in the past year, marijuana use is highest among all age groups followed in descending order by nonmedical use of pain relievers and cocaine usage. The most noteworthy observation is that the 18-25 age group, young drivers who likely have the least driving experience to begin with (a risk factor for accidents), reports the highest use of illicit drugs. All of this may reflect an age group with a high degree of risky behavior.

Tables 2 and 3 each contain the regression estimation results for three different models with pooled data for two years. A Chow test confirmed that the data could be pooled.[9] All models have linear functional forms and the same dependent variable, DEATHRT. Additionally, all models use exactly the same set of non-drug-related explanatory variables. Models 1, 2, and 3 differ based upon the degree of disaggregation in drug types and age groups.

The estimation results in Table 2 are based on drug usage variables aggregated across age groups, all persons 12 years of age or older. Distinctions are made between time periods of last reported usage, within last month or within last year. Table 3 results involve estimations utilizing the same drug categories with a set of disaggregated age categories. Those age groups are 12 to 17, 18 to 25, and 26 years or older. Based on R2 statistics, all of the models in Tables 2 and 3 explain more than three-quarters of the variation in DEATHRT.

The results for the non-drug related independent variables do not change with the level of aggregation for the drug variables. Consequently, these results are reported without identifying the specific model.

INCOME is statistically significant and negatively related to DEATHRT in all six models.[10] These results suggest that better economic conditions increase the demand for safety, perhaps reflecting a higher opportunity cost of an accident and fewer fataly results. This finding is consistent with previous ones based upon pooled cross-section, time-series data.

Where (the location) a person drives influences DEATHRT. All six models reveal statistically significant evidence that as the ratio of rural to urban driving increases, so does the fatality rate. Rural driving conditions may differ in a number of ways: roads may be less congested, permitting higher speeds; road conditions may differ with respect to road surface and lighting; and rural settings may offer fewer nearby medical options in the event of an accident.

Higher temperatures and presumed better driving conditions are positively related to highway fatalities. Temperature may influence the driver's level of attention and visibility (sunlight) as well as vehicle speed. The result is significant across all six models. Precipitation, however, has a statistically insignificant impact on the death rate.

Faster speeds make roads less safe and increase the number of fatalities. Across all six models, SPEEDLIM reveals the anticipated positive sign and is statistically significant.

Table 1: Summary Statistics of Variables

Variable	Minimum	Maximum	Mean	Standard Deviation
DEATHRT	5.776	20.071	11.948	3.204
INCOME	13,222.20	22,391.75	16,404.16	2,121.19
RURURB	0.082	3.113	0.938	0.773
TEMP	38.300	71.100	52.384	7.526
PRECIP	7.690	75.050	38.684	15.565
SPEEDLIM	65.000	75.000	69.610	3.929
YOUNG	10.091	21.623	13.311	1.950
OLD	9.883	20.451	16.292	1.819
SBELTUSE	67.600	98.000	84.930	7.331
CELLPHN	0.745	1.006	0.877	0.054
ALCOHOL	1.330	4.440	2.387	0.483
IDRUSPMO12+	5.290	13.730	8.579	1.976
IDRUSPMO1217	6.890	13.170	9.941	1.468
IDRUSPMO1825	11.980	35.090	21.213	4.845
IDRUSPMO26+	3.400	10.750	6.243	1.707
MARIJPMO12+	3.110	11.570	6.615	1.831
MARIJPMO1217	3.680	11.510	7.209	1.551
MARIJPMO1825	7.740	32.010	18.115	4.845
MARIJPMO26+	1.900	8.860	4.574	1.483
IDROMPMO12+	2.010	5.510	3.603	0.650
IDROMPMO1217	3.560	5.640	4.505	0.474
IDROMPMO1825	4.980	12.730	8.425	1.660
IDROMPMO26+	1.240	4.350	2.661	0.601
MARIJPYR12+	6.940	16.990	11.105	2.345
MARIJPYR1217	9.270	19.530	13.622	2.423
MARIJPYR1825	17.700	46.350	30.112	6.304
MARIJPYR26+	3.700	12.540	7.527	1.866
COCAIPYR12+	0.970	3.890	1.894	0.576
COCAIPYR1217	0.610	1.500	1.029	0.174
COCAIPYR1825	2.610	10.170	5.330	1.715
COCAIPYR26+	0.580	3.170	1.414	0.494
NMPRPYR12+	3.570	8.140	5.022	0.857
NMPRPYR1217	4.580	9.320	6.719	0.944
NMPRPYR1825	8.480	17.940	12.339	1.946
NMPRPYR26+	2.190	6.200	3.552	0.767

Table 2: U.S. State-Level Regression Estimates of Motor Vehicle Deaths per Vehicle-Mile, 2009–2010, Using Illicit Drug Use Data Aggregated Across Age Groups

(t statistic in parentheses beneath each coefficient)				
Independent Variable	Expected Sign	Dependent Variable: DEATHRT		
		Model 1	Model 2	Model 3
Intercept	?	-6.577	-12.609b	-20.332bb
		(-0.850)	(-1.726)	(-2.753)
INCOME	?	-5.36E-04bb	-3.98E-04bb	-3.34E-04bb
		(-4.443)	(-3.417)	(-2.778)
RURURB	+	1.986aa	2.485aa	2.597aa
		(6.305)	(7.801)	(8.560)
TEMP	+	0.181aa	0.142aa	0.151aa
		(5.167)	(4.200)	(4.844)
PRECIP	-	-0.004	0.010	0.009
		(-0.200)	(0.541)	(0.510)
SPEEDLIM	+	0.179aa	0.184aa	0.172aa
		(2.440)	(2.730)	(2.687)
YOUNG	?	-0.136	-0.160	-0.055
		(-1.133)	(-1.449)	(-0.510)
OLD	?	0.350bb	0.297bb	0.391bb
		(3.189)	(2.892)	(3.975)
SBELTUSE	?	-0.077bb	-0.054bb	-0.038
		(-2.869	(-2.130)	(-1.554)
CELLPHN	+	8.622aa	9.955aa	13.935aa
		(2.021)	(2.509)	(3.566)
ALCOHOL	+	0.330	0.491	0.178
		(0.763)	(1.212)	0.460)
IDRUSPMO12+	+	-0.232		
		(-2.049)		
MARIJPMO12+	+		-0.661	
			(-4.417)	
IDROMPMO12+	+		1.254aa	
			(3.338)	
MARIJPYR12+	+			-0.639
				(-5.598)
COCAIPYR12+	+			1.483aa
				(3.473)
NMPRPYR12+	+			0.861aa
				(3.450)
N		96	96	96
R^2		0.767	0.803	0.827
Adjusted R^2		0.736	0.775	0.800

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

Table 3: U.S. State-Level Regression Estimates of Motor Vehicle Deaths per Vehicle-Mile, 2009–2010, Using Illicit Drug Use Data Disaggregated by Age Groups

(t statistic in parentheses beneath each coefficient)				
Independent Variable	Expected Sign	Dependent Variable: DEATHRT		
		Model 1	Model 2	Model 3
Intercept	?	-6.510	-9.027	-14.138
		(-0.784)	(-1.109)	(-1.610)
INCOME	?	-5.29E-04bb	-4.31E-04bb	-2.85E-04b
		(-3.980)	(-3.335)	(-1.877)
RURURB	+	2.004aa	2.606aa	3.127aa
		(6.196)	(8.006)	(9.086)
TEMP	+	0.178aa	0.119aa	0.108aa
		(4.980)	(3.393)	(3.108)
PRECIP	-	0.001	0.019	0.021
		(0.053)	(1.011)	(1.025)
SPEEDLIM	+	0.173aa	0.184aa	0.142aa
		(2.189)	(2.489)	(1.978)
YOUNG	?	-0.143	-0.131	-0.034
		(-1.159)	(-1.158)	(-0.313)
OLD	?	0.351bb	0.241bb	0.361bb
		(3.159)	(2.284)	(3.747)
SBELTUSE	?	-0.079bb	-0.059bb	-0.047b
		(-2.865)	(-2.323)	(-1.941)
CELLPHN	+	8.643aa	8.833aa	11.090aa
		(1.992)	(2.203)	(2.502)
ALCOHOL	+	0.317	0.370	-0.086
		(0.688)	(0.890)	(-0.216)
IDRUSPMO1825	+	0.096		
		(0.395)		
IDRUSPMO1825	+	-0.081		
		(-0.623)		
IDRUSPMO26+	+	-0.130		
		(-0.403)		
MARIJPMO1217	+		0.135	
			(0.505)	
MARIJPMO1825	+		-0.016	
			(-0.112)	
MARIJPMO26+	+		-0.768	
			(-2.326)	
IDROMPMO1217	+		-0.052	
			(-0.106)	

Table 3 (continued)

Independent Variable	Expected Sign	Dependent Variable: DEATHRT		
		Model 1	Model 2	Model 3
IDROMPMO1825	+		-0.267	
			(-1.348)	
IDROMPMO26+	+		2.008aa	
			(3.594)	
MARIJPYR1217	+			0.434aa
				(2.200)
MARIJPYR1825	+			-0.280
				(-2.515)
MARIJPYR26+	+			-0.379
				(-1.368)
COCAIPYR1217	+			1.520
				(0.969)
COCAIPYR1825	+			-0.546
				(-1.622)
COCAIPYR26+	+			2.807aa
				(3.689)
NMPRPYR1217	+			-0.525
				(-1.536)
NMPRPYR1825	+			0.262
				(1.262)
NMPRPYR26+	+			0.960a
				(1.508)
N		96	96	96
R2		0.767	0.817	0.852
Adjusted R2		0.730	0.780	0.815

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

The age of the driving population is related to the death rate. There is strong evidence that the percentage of older drivers has a statistically significant and positive relationship with highway fatalities. Slower reflexes and deteriorating eyesight, among other reasons, may be factors. Conversely, the size of the pool of younger drivers is not linearly related to DEATHRT. In all six models, the coefficient for YOUNG is negative, yet in no case is the estimate statistically significant.

In this analysis, previous research findings by NHTSA are corroborated. Seat belt use has a life-saving effect. Across all six models, the SBELTUSE coefficients are negative, and in only one case is the coefficient not statistically significant.

Cell phone usage, in this analysis, contributes to less safe driving conditions. CELLPHN's coefficient is always positive and statistically significant. The life-taking effect of a cell phone may result from driver distractions during calls, as well as physical challenges to make and answer calls. Evidently, the possible life-saving impact of the cell phone (faster response times) is not strong in this data set. The models included here assumed a linear effect of cell phone use on DEATHRT.

A large body of previous research supports the negative consequences of alcohol consumption on highway safety. In all but one model, Model 3 of Table 3, the positive coefficients are consistent with expectations. Higher levels of alcohol use are associated with higher motor vehicle death rates. None of the six models includes evidence of a statistically significant relationship. While the negative sign for ALCOHOL in Model 3 runs counter to conventional wisdom that greater alcohol consumption is associated with more fatalities, the estimated coefficient is not statistically significant.

Table 2 presents the results of the age aggregated drug use models. The models include drug usage in the past month and the past year. In Model 1, the anticipated positive sign for the coefficient of IDRUSPM012+ does not occur. Aggregate illicit drug use in the past month by individuals 12 or older does not increase the highway death rate.

When illicit drug use is disaggregated by drug type in Table 2, differences in road safety appear. Models 2 and 3 reveal illicit drugs other than marijuana increase highway fatalities for users within both the past month and the last year. Statistically significant positive relationships exist for the variables IDROMPMO12+, COCAIPYR12+, and NMPRPYR12+. In Table 2 models, marijuana use does not make roads less safe, as all variables accounting for marijuana have negative coefficients with t statistics that are large in absolute value.

Models in Table 3 include variables to disaggregate age (12-17, 18-25, and 26+) and drug use type (marijuana, cocaine, and nonmedical use of pain relievers). In most cases, illicit drug use by the youngest drivers increases highway fatalities. Four of the six variables with the suffix 1217 reveal positive relationships. Of these, only marijuana is statistically significant in Model 3, the model with the most disaggregated groups. Evidently, the combination of the most inexperienced drivers and the age group most likely to be exploring drug use increases the motor vehicle fatality rate.

Only one of the six variables with the suffix 1825 (NMPRPYR1825 in Model 3) has a positive estimated coefficient. This implies that nonmedical use of pain relievers by those aged 18 to 25 is directly associated with the motor vehicle fatality rate, although the finding is not statistically significant. Young professionals may be making prudent decisions (e.g., utilizing designated drivers) about operating vehicles under the influence of drugs.

Three of the drug use variables with the suffix 26+ have statistically significant positive estimated coefficients: IDROMPMO26+ in Model 2 and both COCAIPYR26+ and NMPRPYR26+ in Model 3. These results indicate that the motor vehicle death rate is directly linked to usage of cocaine and nonmedical pain relievers by individuals 26 and over. Apparently, these two drugs adversely affect the driving ability of older motorists.

A noteworthy finding of this study is that the impact on highway safety of drug use varies by drug type and age group. A statistically significant life-taking effect is found for marijuana usage by those aged 12−17 and for consumption of cocaine and nonmedical pain relievers by those aged 26 and over.

SUMMARY

This paper is an effort to better understand the factors that influence motor vehicle deaths across U.S. states. Its contribution is adding illicit drug usage to a set of factors that explain deaths per vehicle-mile. Six models using estimated annual data for two years (2009 and 2010) for U.S. states, provide results generally consistent with previous findings.

Estimation results pertaining to the influences of several explanatory factors are robust across the models that include them. Negatively related to the fatality rate and statistically significant are real per capita income and seat belt use. Statistically significant positive associations with the highway death rate are found for the ratio of rural to urban driving, temperature, speed limit, percentage of older drivers, and cell phone usage.

One set of regression estimations are based on drug usage variables aggregated across age groups, all persons 12 years of age or older. These estimates reveal that use of both cocaine and nonmedical pain relievers increases highway fatalities. Counter to expectations, marijuana use does not make roads less safe as all variables accounting for marijuana have negative coefficients with t statistics that are large in absolute value.

A second set of regression estimations employs drug usage variables disaggregated by age group (12−17 years, 18−25 years, and 26 years and over). These estimates reveal that the effect of illicit drug usage on motor vehicle deaths differs across age groups. Marijuana use among those aged 12−17 has a life-taking impact. In the age group 26 years old and over there is a different pattern in that use of both cocaine and nonmedical pain relievers contributes to an increase in highway fatalities.

The results of this research bring certain areas to the attention of policy makers and lawmakers. One area to consider is the information sharing boundary between the medical community, as a drug prescribing group, and the law enforcement group. There is increasing activity at the state level on the issue of liberalizing marijuana use, primarily for medical purposes.[11] Given the findings reported here, proposed legislation should include deliberation about the different impacts on highway safety of such use across age groups. In particular, for young patients on a medical marijuana treatment program, it may be appropriate to consider an alternative minimum age for driving privileges. Further, the law enforcement community can work with the medical community to develop guidelines for vehicle operation while using medical marijuana. This issue becomes further complicated as individual states make decisions about medical marijuana and drivers cross state lines in their travels.

Greater emphasis can be placed on impaired driving while broadening the classification of such driving. Just as prescription drugs are monitored for overdoses and addictions, inappropriate use of prescription drugs has highway safety implications. This problem can be expected to increase with an aging driving population and a more widespread use of prescriptions for all types of medical conditions. The highway safety issues further intensify because of the consumption of cocaine and nonmedical pain relievers by older drivers.

While devices currently exist to detect alcohol levels during a traffic stop, police officers have no corresponding protocol for other substances that may cause driver impairment. Field tests represent the primary impairment detection strategy. Consequently, law enforcement officials may be making decisions with limited information. Greater research efforts to develop drug detection counterparts to the breathalyzer would help law enforcement professionals. Policy makers play a role, as they should decide how to balance patient privacy rights against a common good of highway safety.

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Endnotes

1. Loeb, Talley, and Zlatoper (1994) summarize results of several empirical studies of highway death determinants until that point in time. Blattenberger, Fowles and Loeb (2013) summarize research that is more recent.

2. Peltzman (1975, p. 681) uses "driving intensity" to refer to greater "speed, thrills, etc.," that drivers gain by giving up some safety.

3. Data on cell phone use while driving are unavailable at the state level for 2009 and 2010. Therefore, information on this activity for the population in general is utilized in this analysis. The assumption is made here that the behavior of drivers with regard to this activity is highly correlated with that in the general population.

4. Data on alcoholic intoxication while driving are unavailable at the state level for 2009 and 2010. Therefore, information on this activity for the population in general is utilized in this analysis. The assumption is made here that the behavior of drivers with regards to this activity is highly correlated with that in the general population.

5. Values used for 2009 are 2008−2009 estimates, and values utilized for 2010 are 2009−2010 estimates.

6. Data on drug use while driving are unavailable at the state level for 2009 and 2010. Therefore, information on this activity for the population in general is utilized in this analysis. The assumption is made here that the behavior of drivers with regard to this activity is highly correlated with that in the general population.

7. Illicit drugs include marijuana/hashish, cocaine (including crack), heroin, hallucinogens, inhalants, or prescription-type psychotherapeutics used nonmedically.

8. Illicit drugs other than marijuana include cocaine (including crack), heroin, hallucinogens, inhalants, or prescription-type psychotherapeutics used nonmedically.

9. A Chow test can determine whether a structural change in the relationship between the highway death rate and the explanatory variables occurred between 2009 and 2010. This test was conducted for each model. The results confirmed that the data for the two years could be pooled. See Gujarati and Porter (2009, pp. 254−259) for a discussion of the Chow test.

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

11. According to ProCon.org (2015), during the years 2009 and 2010, marijuana was legal for medical purposes for at least a portion of the time in 15 states.

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Calibration of the Highway Safety Manual Given Safety Performance Functions for Rural Multilane Segments and Intersections in Kansas

by Syeda Rubaiyat Aziz and Sunanda Dissanayake

The Highway Safety Manual (HSM) provides models and methodologies for safety evaluation and prediction of safety performance of various types of roadways. However, predictive methods in the HSM are of limited use if they are not calibrated for local conditions. In this study, calibration procedures given in the HSM were followed for rural segments and intersections in Kansas. Results indicated that HSM overpredicts fatal and injury crashes and underpredicts total crashes on rural multilane roadway segments in Kansas. Therefore, existing safety performance functions (SPFs) must be adjusted for Kansas conditions, in order to increase accuracy of crash prediction. This study examined a way to adjust HSM calibration procedures by development of new regression coefficients for existing HSM-given SPF. Final calibration factors obtained through modified SPFs indicated significant improvement in crash prediction for rural multilane segments in Kansas. Additionally, obtained calibration factors indicated that the HSM is capable of predicting crashes at intersections at satisfactory level.

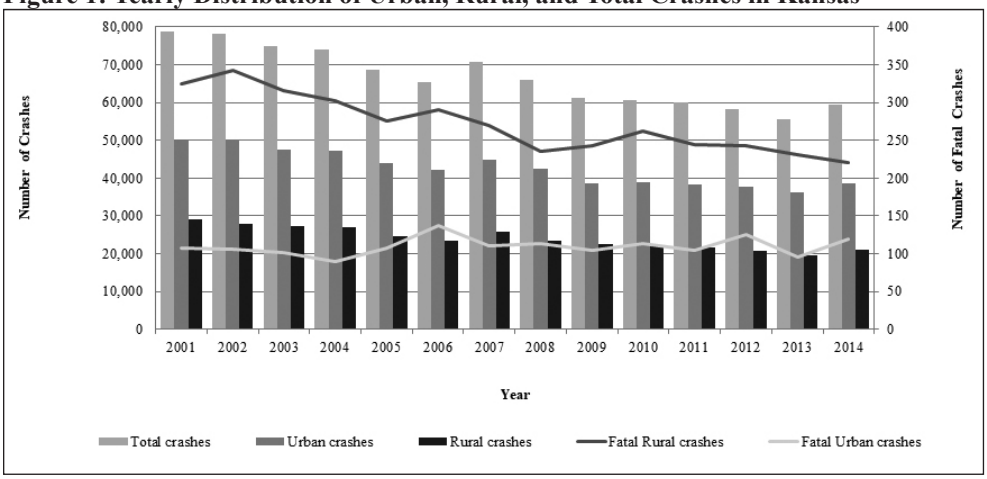
INTRODUCTION

A report in 2016 ranked motor vehicle crashes as one of the top ten causes of death in the United States (Heron 2016). Relative to 2011, fatal highway crashes increased by 1.7% to 29,989 in 2014, equivalent to an average of 90 daily fatalities (NHTSA 2015). In Kansas, rural roads account for 90.3% of the 226,504 km (140,476 miles) of total roadway (KDOT 2015). Travel on rural roads accounts for 48.5% of all vehicle miles (60% for state highways) (KDOT 2015). According to 2014 Kansas crash data, 35% of total vehicle crashes occurred on rural roads, while fatal crashes on rural roads accounted for over 66% of total fatal crashes on rural and urban roads (KDOT 2015). Figure 1 shows the distribution of rural, urban, fatal rural, fatal urban, and total crashes over a 14-year period, indicating higher fatal crashes occurring on the rural highways of Kansas. These fatality records are a matter of concern to highway safety professionals because they show that the proportion of high-level injury crashes is most problematic in rural areas. In general, Kansas has a low population density, and a majority of the roadways are located in rural areas. Because of the significant amount of travel on rural roads and the relatively alarming safety records of rural roads compared with urban roads, effective crash prevention methods must be developed.

In 2010, the American Association of State Highway and Transport Officials (AASHTO) published the Highway Safety Manual (HSM), which is the culmination of decades of safety research and practices (AASHTO 2010). The HSM presents models and methodologies for analyzing highway types based on safety. Procedures to calibrate predictive models are provided in Part C – Appendix A of the HSM (AASHTO 2010). Crash predictive methods in the HSM allow planners, designers, and reviewers to comprehensively assess expected safety performance of roadway design using methodologies endorsed by the Federal Highway Administration (FHWA). Predictive methods in the HSM were developed based on national trends and statistics or data from Texas, California, Minnesota, New York, and Washington from 1991 through 1998 (Bahar 2014). As a result, these methodologies are of limited use if they are not calibrated for individual jurisdictions or local conditions. Calibration ensures achievement of the most realistic and reliable crash estimates.

As safety conditions change with time, transportation agencies must use calibrated HSM models. At the time of this study, the Kansas Department of Transportation (KDOT) was able to apply the rural two-lane model from the HSM because a study had been completed to calibrate such facilities (Lubliner and Schrock 2012). However, when the analysis of a multilane facility was requested, it could not have been completed without calibration. Therefore, an acceptable method to predict crashes for rural multilane highway segments and intersections in Kansas must be identified or developed. Availability of an effective safety performance function (SPF) that predicts the number of crashes on a section of highway and identifies potential severe crash locations would enable designers to create safer roads and decrease roadway construction and maintenance costs if, for example, 2.4-m (8 ft.) shoulders were determined to be as beneficial as 3-m (10 ft.) shoulders.

Figure 1: Yearly Distribution of Urban, Rural, and Total Crashes in Kansas



The predictive methods given in chapter 11 of the HSM focus on rural multilane highways. According to the HSM, rural four-lane highways are categorized as rural multilane highways, and six-lane divided highways are not considered under rural multilane segments category. Therefore, this study was limited to calibrations of rural four-lane divided and undivided highways.

The objective of this study was to analyze HSM calibration procedures for rural four-lane segment and intersection models in Kansas. If the crash prediction was inadequate after performing calibration, then the methodology will be modified to allow the HSM to more accurately reflect local conditions of Kansas. This paper begins with background discussion of the HSM methodology, followed by past research conducted in similar contexts. A subsequent section discusses the HSM methodology and various data used in the analysis. Analysis results are presented in a following section, and the last section summarizes and concludes the study with future recommendations.

LITERATURE REVIEW

The HSM requires a three-step process in order to predict the expected number of crashes for any highway facility given a set of values for input variables. The first step requires calculation of the SPF, which is the regression equation that calculates the dependent variable, or predicted crash frequency, based on independent variables. The second step requires multiplying by crash modification factors (CMFs) for each independent variable. In the third step, the calibration factor (C) is obtained by dividing the number of observed crashes by the number of predicted crashes (AASHTO 2010). Since the first edition of the HSM provided general methodologies and statistical tools for estimating expected numbers of crashes, researchers have attempted to validate

and apply the methodologies to particular areas and specific roadway facility type. In particular, safety effectiveness of multiple roadway treatments has become essential for the HSM methodology validation. This section reviews and discusses recent studies in HSM calibration.

Qin et al. (2014) applied HSM methodology for rural two-lane, two-way highway segments in South Dakota. Results showed that South Dakota-specific crash type distribution for CMFs differed significantly from default crash proportions presented in the HSM. For rural two-lane roadways, the HSM method without modification underestimated South Dakota crashes by 35%. Mehta and Lou (2013) evaluated the applicability of the HSM predictive methods for two-lane, two-way rural highways and four-lane divided highways in Alabama. In their study, the HSM-given method for calibration factor estimation was proven to be a satisfactory approach since it fits the Alabama data well, although the approach did not predict crash scenario as well as the optimal state-specific SPF. In a study conducted by Sun et al. (2013), results indicated close agreement between the number of crashes predicted by the HSM and the number of crashes observed in Missouri for site types.

Sun et al. (2011) calibrated the SPF for rural multilane highway segments in Louisiana. The calibration parameters indicated that the predicted model from the HSM for rural divided multilane highways underestimated the number of expected crashes. Srinivasan and Carter (2011) compared the performance of SPF developed using negative binomial regression to the HSM methodologies for roadways in North Carolina. They found that segments within the influence of at-grade intersections and railroad grade crossings (250 ft. on either side of at-grade intersections or railroad grade crossings) significantly affected crash prediction on rural segments. Jalayer et al. (2015) provided a revised method to help state and local agencies predict the number of crashes without developing new calibration factors. Srinivasan and Bauer (2013) used the negative binomial model for the SPF, requiring the evaluation of average annual daily traffic (AADT) as the mandatory variable, while other factors (i.e., roadway geometry, traffic control features, etc.) were left to the discretion of the state DOT.

Lubliner and Schrock (2012) analyzed predictive methods for calibrating rural two-lane segments for Kansas highways. Based on study results, combined statewide calibration of total crashes was recommended for aggregate analyses that include multiple sections. The calibration factor obtained while considering animal crash frequency by county as a variable was recommended for project-level analysis performed on Kansas rural two-lane highways.

Lord et al. (2008) developed a methodology that predicts the SPF of elements considered in the planning, design, and operation of non-limited-access rural highways. The significance and influence of sample size were shown to significantly affect the calibration process. Shin et al. (2014) completed the calibration process for SPFs in the HSM for the Maryland Department of Transportation. Their study calculated the confidence interval for a range of calibration factors that would contain 90% of the population. Another study (Banihashemi 2012) that used data from the state of Washington investigated the ideal sample size for calibrating the HSM models and sensitivity related to sizes of samples used for the HSM calibration factors by evaluating factor qualities. Results showed that a single criterion for sample size may not be the ideal methodology.

Bornheimer et al. (2012) tested the original HSM-given crash prediction model (CPM) to state-specific calibrated CPMs and new, independent CPMs to determine the best model for rural two-lane highways in Kansas. Almost 483 km (300 miles) of highway geometric data were collected to create the new models using negative binomial regression. Lane width and roadside hazard rating consistently were the most significant variables in each model. These models were compared to CPMs calibrated for use by the HSM using nine validation segments (Bornheimer et al. 2012). However, comparison was difficult due to the large amount of animal-related crashes, accounting for 58.9% of crashes on Kansas highways.

A recent study conducted by Kweon et al. (2014) examined ways to customize the HSM procedures and then developed guidance to help highway agencies choose optimum customization options for their jurisdictions. Based on empirical data, the guidance recommended the best option

for crash prediction for Virginia. The developed guidance flowchart can be used by agencies interested in customizing the HSM procedures. The developed flowchart can also be applied in addition to expert opinion and data analysis; however, increased reliance on data analysis would require additional time and resources (Kweon et al. 2014).

METHODOLOGY

Because the SPF significantly affects crash prediction, SPF calibration is one of the most critical and effective steps in the prediction process. Ideally, base conditions should represent typical roadway geometries, guaranteeing a sizable sample to develop statistically robust models. However, the most representative roadway type may vary by state or region. If the sample size that matches base conditions is small, then SPF calibration may not be rigorous or sufficiently representative of the larger population.

The standard approach for obtaining calibration factors given in the HSM for roadway segments can be summarized in the following five steps:

- Identify desired facility types.
- Select segments from the desired facility types.
- Collect required data for those segments.
- Apply the HSM predictive models.
- Compute calibration factors.

Facility types considered in the current study included rural four-lane divided and undivided segments. All segments under these categories were selected as analysis locations, and then the HSM methodology was followed for calibration, as described in the following sections.

Safety Performance Function

SPFs are regression equations that calculate the dependent variable, or predicted crash frequency, based on independent variables. Because this study attempted to determine suitability of HSM-specified methods, SPFs in the HSM were used to calculate the number of predicted crashes (AASHTO 2010). SPFs in the HSM differ from SPFs typically found in other crash prediction tools because they predict an average crash frequency under "base conditions" defined in the HSM. The base conditions for rural four-lane divided and undivided highways are given in Table 1. CMFs convert predictions under base conditions made by SPFs into predictions under existing conditions (AASHTO 2010). SPF for a rural four-lane highway segment is estimated as follows:

$$(1)\ N_{SPF}=e^{[a+b\times\ln(AADT)+\ln(L)]}$$

where, N_{SPF} is the base total expected average crash frequency for the rural segment, e is the exponential, ln is the natural logarithm, *AADT* is the Average Annual Daily Traffic on the highway segment, *L* is the length of the highway segment (miles), and *a* and *b* are the regression coefficients.

Table 1: Base Condition for SPFs

Four-lane Divided Highways		Four-lane Undivided Highways	
Variable	Base Condition	Variable	Base Condition
Lane width	12 feet	Lane width	12 feet
Right shoulder width	8 feet	Shoulder width and type	6 feet, paved
Median Width	30 feet	Side-slope	1:7 or flatter
Lighting	None	Lighting	None
Automated Speed Enforcement	None	Automated Speed Enforcement	None

The SPF for rural intersections has two alternative functional forms in the HSM: one form considers AADT on major and minor road approaches (Equation 2), and the other form considers combined AADT on major and minor road approaches (Equation 3).

(2) $N_{spf\,int} = \exp[a + b \times \ln(AADT_{maj} + c \times \ln(AADT_{min})]$

(3) $N_{spf\,int} = \exp[a + d \times \ln(AADT_{total})]$

where, $N_{spf\ int}$ is the SPF estimate of intersection-related expected average crash frequency for base conditions, exp is the exponential, $AADT_{maj}$ is the AADT (vehicles per day) for major-road approaches, ln is the natural logarithm, $AADT_{min}$ is the AADT (vehicles per day) for minor-road approaches, $AADT_{total}$ is the AADT (vehicles per day) for major-road and minor-road combined approaches, and *a, b, c,* and *d* are the regression coefficients.

Crash Modification Factors

The SPF is multiplied by CMFs for each independent variable given in the HSM, as shown in Equation 4. CMFs pertain only to changes in design or operation characteristics (e.g., lane width and shoulder width) typically under the control of highway engineers and designers as compared with characteristics such as climate, driver behavior, and crash reporting threshold, which could not be controlled (Kweon et al. 2014).

(4) $N_{Predicted} = N_{SPF} \times C_r \times (CMF_1 \times CMF_2 \times ..... \times CMF_i)$

where, $N_{Predicted}$ is the adjusted number of predicted crash frequency, N_{SPF} is the total predicted crash frequency under base condition, CMF_i is the CMFs for i^{th} variable, and C_r is the calibration factor.

CMF for the presence of lighting was calculated using Equation 5.

(5) $CMF_{lighting} = 1 - [(1 - 0.72 \times P_{inr} - 0.83 \times P_{pnr}) \times P_{nr}]$

where, $CMF_{lighting}$ is the crash modification factor for presence of lighting at a segment, P_{inr} is the proportion of nighttime crashes for unlighted segments that involve fatality/injury, P_{pnr} is the proportion of nighttime crashes for unlighted segments that involve property damage only (PDO) crashes, and P_{nr} is the proportion of total crashes for unlighted segments that occur at night.

CMFs for intersection skew angle (The difference between 90 degrees and the smallest acute angle between the intersection legs is referred to as the intersection skew angle.), presence of right

turn lane on major road, presence of left-turn lane on major road, and presence of lighting posts were obtained using charts and equations provided in the HSM. SPFs at each intersection were multiplied by corresponding CMFs for all intersection-related attributes.

Calibration Factor

SPFs in the HSM were developed using data from jurisdictions and/or time periods rather than where or when such SPFs should be utilized. For example, default HSM-SPFs for rural multilane highways were developed using data from Texas, California, Minnesota, New York, and Washington from 1991 through 1998 (Bahar 2014). However, the general level of crash frequencies may vary substantially from one jurisdiction to another and/or from one year to another due to changes in climate, driver behavior, and crash reporting thresholds among many other changes (AASHTO 2010). Therefore, in order to produce predictions that reflect levels of crash frequencies in jurisdictions and/or years of interest, the predicted number of crash frequencies must be adjusted using the calibration factor. Calibration factors should be determined for each facility-site type. Calibration factor (C_r) is obtained by dividing the total number of observed crashes by the total number of predicted crashes, as shown in Equation 6. Observed crash frequencies are obtained using a crash database, and predicted crashes are obtained using HSM methodology.

$$(6)\quad C_r = \frac{\Sigma\text{Observed crashes}}{\Sigma\text{Predicted crashes}}$$

ANALYSIS DATA

This study obtained highway crash data from the Kansas Crash Analysis and Reporting System (KCARS) database, consisting of all police-reported crashes in Kansas (KDOT (b) 2017). Geometric data were obtained from the state's highway inventory database, Control Section Analysis System (CANSYS), which provided the AADT volume for 2013, the most recent year for which data were available at the beginning of the study (KDOT (a) 2017). Accordingly, the study duration was determined to be 2011–2013.

Kansas Crash Analysis and Reporting System

The KCARS database consists of several tables that contain details of each crash occurring in Kansas roadways, such as crash location, light conditions, weather conditions, road surface type, road conditions, road character, road class, road maintenance information, date of crash, time of crash, day of crash, accident class, and manner of collision. Multiple tables were combined and queries were run to filter out crashes on rural multilane highways and five levels of crash severity.

Control Section Analysis System

The CANSYS database contains information about the geometrics, condition, and extent of the more than 16,093 km (10,000 miles) of roads in Kansas's highway system, as well as a small proportion of local roadways not on the state highway system.

CANSYS data are collected at random intervals from various sources, and the database is typically used for high-level analyses for network screening and trend evaluations. For this study, data were sorted by route name and county so that every mile was accounted for, but no data were counted twice. Based on data requested, county mile posts of beginning and ending of segments, coordinates of beginning and ending mile posts of segments, lane width, left shoulder width, right shoulder width, median width, side slope (slope of the cut or fill expressed as the ratio of horizontal distance to vertical distance), and AADT for 2013 were obtained from this database. CANSYS

also contains the route ID, route direction, number of lanes, and outer shoulder and inner shoulder description. All the sources of different variables used in the study are summarized in Table 2. The HSM considers the presence of automated speed enforcement as optional (desired) data, and automated speed enforcement is not used in Kansas. Once all data were obtained, they were used in accordance with the HSM methodology.

Table 2: Data Sources for Rural Four-Lane Segments used in Calibration

Data Description	Source
AADT	CANSYS
Lane Width	CANSYS
Median Width	CANSYS
Shoulder Width	CANSYS
Sideslope	CANSYS
Presence of Lighting	Google Maps®
Number of Crashes	KCARS
Presence of Automated Speed Enforcement	Not Applicable
Segment locations	CANSYS

STUDY SEGMENTS & INTERSECTIONS

A total of 281 rural four-lane divided (4D) segments and 83 four-lane undivided (4U) segments obtained from CANSYS database were used for calibration in conjunction with HSM methodology. The rural four-lane segments were present on both Kansas and US highways. The number of observed crashes for all 4D segments in Kansas was 910 per year, and the number of crashes for 4U segments was 36 per year. All segments met the HSM segment length requirement of 0.16 km (0.1 mile). Lane width, shoulder width, median width, and side slope were obtained from the CANSYS database.

Figures 2 (a) and (b) show the distribution of 4D and 4U segments, respectively, within the state of Kansas. The markers indicate beginning and end of a roadway segment, respectively, and a small dot indicates a crash location. One segment on each figure was zoomed for clear illustration of that particular section.

The calibration of rural multilane intersections using HSM methodology pertains to a three-leg intersection with minor-road stop control (3ST), four-leg intersection with minor-road stop control (4ST), and four-leg signalized intersection (4SG). To date, the 4SG intersection calibration methodology is not complete in HSM, so only 4ST and 3ST intersections were calibrated in this study. The intersections were preliminarily obtained from the CANSYS database. However, the CANSYS database did not have a complete list of intersections available at the time of this study, and most of the required intersection-related information was missing. Therefore, existing intersections were found via Google Maps®.

Each intersection was zoomed to Street View in these maps to obtain corresponding intersection skew angle, presence of right-turn lane on major road, presence of left-turn lane on major road, and presence of lighting posts at intersections. Several intersections were difficult to determine whether they were 3ST or 4ST, so the identified intersections were cross-checked using KDOT-monitored videologs.

After completing data collection via Google Maps and KDOT videologs, a total of 199 4ST intersections and 65 3ST intersections at minor approaches were considered in the calibration. Because the HSM provides no precise guidelines regarding the number of observed crashes at intersections, observed crashes at intersections were counted using two methods.[1] The first

method considered crashes within an intersection-box of 300 ft. along each approach leading to the intersections regardless of whether or not crashes were intersection-related. Figure 3 shows an example of an intersection-box at an intersection. The second method considered the "intersection related" column in the KCARS database, which distinguishes whether or not crashes are intersection-related irrespective of crash distance from named intersections.

Figure 2: Rural Multilane Segments and Crash Locations in Kansas

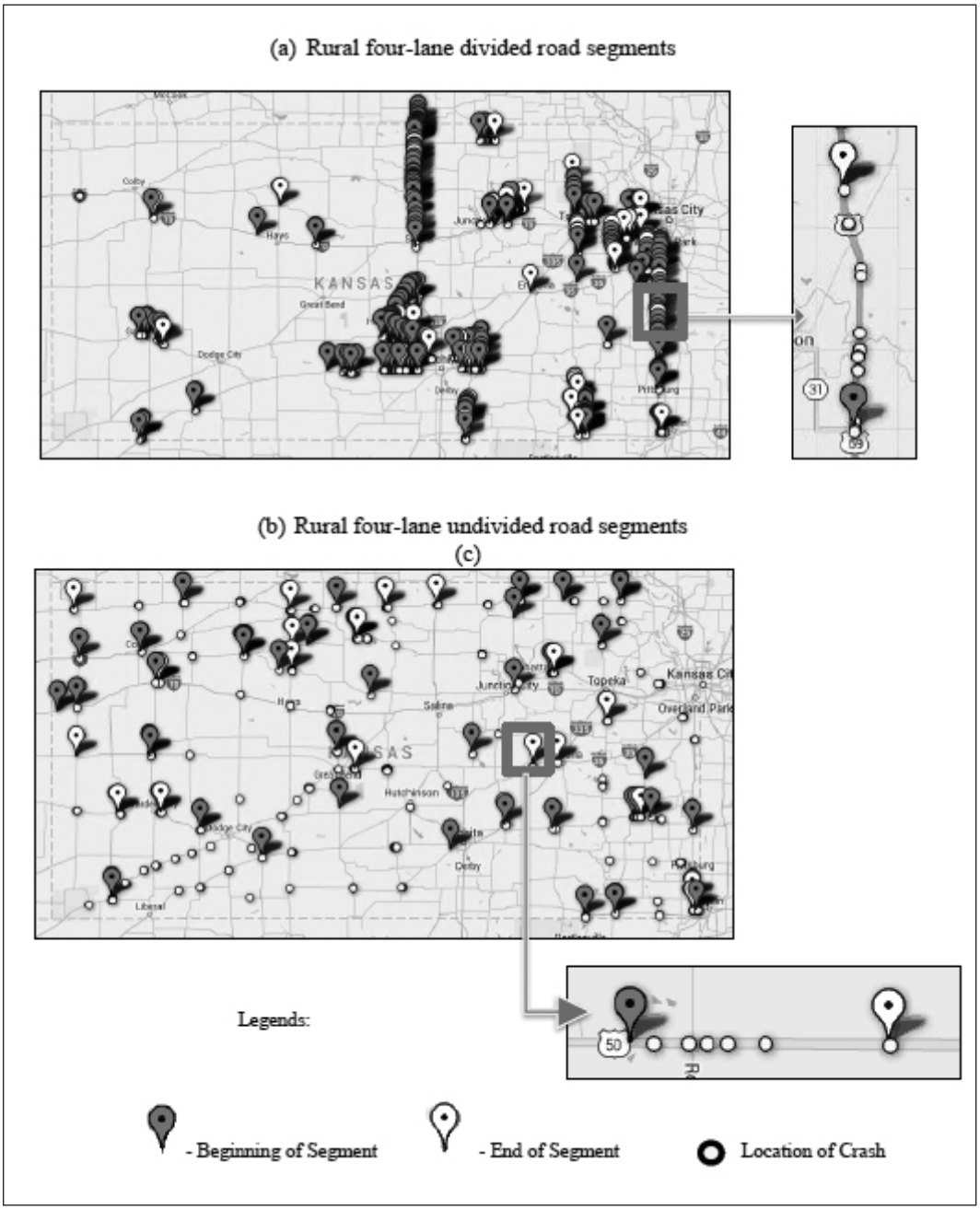


Figure 3: Intersection-Box Demonstration

ANALYSIS AND RESULTS

Crash Situation in Rural Four-lane Highways in Kansas

Table 3 demonstrates distribution by collision type for specific crash severity levels on rural four-lane roadway segments. This table also compares the Kansas crashes to the default distribution given in the HSM (AASHTO 2010). HSM recommends obtaining jurisdiction-specific crash proportions for calibrations. The Kansas Motor Vehicle Accident Report contains five categories for light conditions: daylight; dawn; dusk; dark: street lights on, dark: no street lights; and unknown. Crashes for daylight and dawn were assigned to the daylight category. Once the crashes were categorized as fatal, injury, or PDO, the crashes were assigned using collision types from the Kansas Motor Vehicle Accident Report.

HSM Calibration – Four-lane Segments

In order to perform calibration of SPFs given in the HSM, study segments were obtained from the CANSYS database. Figures 4 and 5 show the distribution of crashes throughout the 4D and 4U segments, respectively. Total crashes for 4D greatly exceeded the HSM requirement of 100 crashes per year, but all 4U segments combined did not meet this requirement. However there were more than 30-50 segments meeting the HSM requirement for segment length. Therefore, the HSM recommendation to consider all available segments with existing crashes was followed for this study (AASHTO 2010).

Table 3: Comparison of Crashes for Kansas Rural Four-Lane Highways by Collison Type

Collision Type	2011			2012			2013			3-year Kansas Average			HSM Default Value		
	Total (%)	Fatal and Injury (%)	PDO (%)	Total (%)	Fatal and Injury (%)	PDO (%)	Total (%)	Fatal and Injury (%)	PDO (%)	Total (%)	Fatal and Injury (%)	PDO (%)	Total (%)	Fatal and Injury (%)	PDO (%)
Head on	9.47	12.70	3.00	8.03	11.95	0.50	8.70	13.05	0.00	8.73	12.57	1.17	0.60	1.30	0.20
Rear End	34.67	33.00	38.10	29.43	23.35	41.60	37.67	32.85	47.30	33.92	29.73	42.33	11.60	16.30	8.80
Sideswipe	16.27	7.05	34.10	18.93	11.70	33.30	15.07	7.60	30.00	16.76	8.78	32.47	4.30	2.70	5.30
Angle	36.73	46.70	16.80	40.63	52.80	16.30	35.27	44.95	15.90	37.54	48.15	16.33	4.30	4.80	4.10
Other	2.87	0.55	8.10	2.97	0.30	8.30	3.20	1.50	6.60	3.01	0.78	7.67	79.20	74.90	81.60

Figure 4: Distribution of Crash Frequency on Four-Lane Divided Segments in Kansas

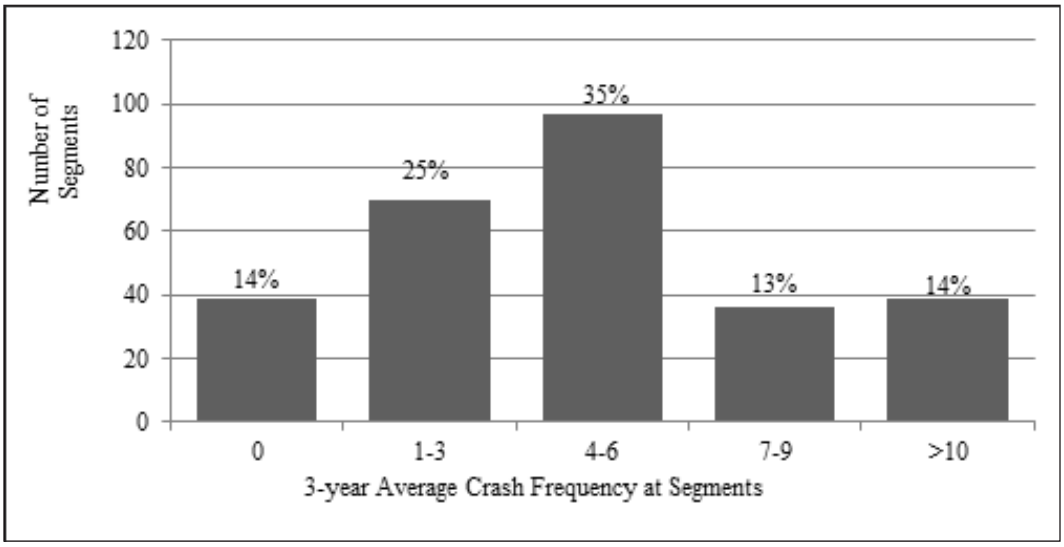
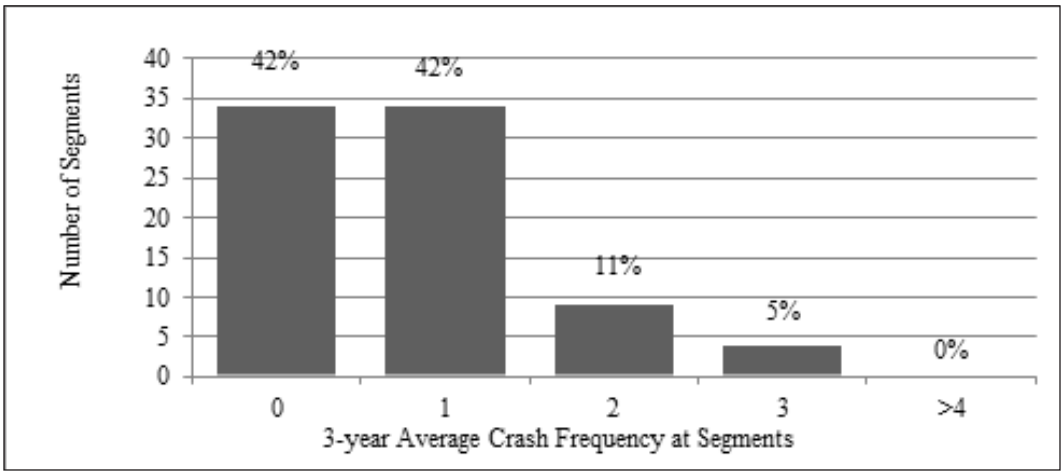


Figure 5: Distribution of Crash Frequency on Four-Lane Undivided Segments in Kansas



Descriptive statistics of 4D and 4U segment characteristics are shown in Table 4. The average length of 4D segments (2.47 km) was well above the minimum length of 0.16 km (0.1 miles), with segment lengths ranging between 0.16 km and 13.90 km (0.1 miles and 8.63 miles). Traffic volumes averaged 8,000 vpd, with a maximum of 31,000 vpd. Segments were relatively uniform with respect to lane and shoulder width, but they showed variation with respect to median width. The average number of crashes was 9.72, ranging between zero and 98 crashes. Seventy-eight segments had lighting present, but no automated speed enforcement was applicable for any highways in Kansas.

The average length of 4U segments was 0.29 km, which is very close to the HSM required minimum segment length of 0.16 km. Segments ranged in length from 0.16 km to 0.68 km Segments were relatively uniform with respect to lane width, but they showed variation with respect to shoulder width. The average number of crashes was 1.29, ranging between zero and 7 crashes. The total number of crashes was 107 for three years, or an average of 36 crashes per year, which was less than the HSM's recommendation of 100 crashes per year. Because this study considered all

possible 4U segments in Kansas instead of only a sample, calibration could be performed with these segments, even with limited number of crashes (AASHTO 2010).

Table 4: Descriptive Statistics for Rural Four-Lane Segments

Roadway Type	Description	Average	Minimum	Maximum	Std. Dev.
4D	Length (km)	2.47	0.16	13.90	2.49
	AADT (2013)	8,000	490	31,000	4,657
	Left lane width (m)	3.68	3.35	6.40	0.18
	Right lane width (m)	3.68	3.35	6.40	0.18
	Left paved shoulder width (m)	1.73	0	3.00	0.44
	Right paved shoulder width (m)	2.85	0	3.00	0.56
	Median width (m)	9.34	1.50	46.33	4.81
	Number of crashes	9.72	0	98.0	11.90
	Presence of lighting	0.28	0	1	0.44
4U	Length (km)	0.29	0.16	0.68	0.11
	AADT (2013)	4,787	520	12,700	3,060
	Left lane width (m)	3.72	3.66	3.96	0.13
	Right lane width (m)	3.72	3.66	3.96	0.13
	Left paved shoulder width (m)	2.00	0	3.05	1.34
	Right paved shoulder width (m)	1.86	0	3.05	1.37
	Sideslope	-	1:2	1:6	-
	Number of crashes	1.29	0	7.0	1.55
	Presence of lighting	0.24	0	1	0.43

After obtaining the observed crash frequency at each segment using the crash database, the predicted number of crashes was estimated. For each segment, the HSM-given SPF was obtained using Equation 1. CMFs were obtained for lane width, shoulder width, median width, and sideslope for each segment using charts and equations provided in the HSM. CMF for median width is required for 4D segments only and CMF for sideslope is required for 4U segments only.

Chapter 11 of the HSM provides tables to obtain CMFs that correspond to lane width, shoulder width, median width, and sideslope. As demonstrated in Equation 3, the CMF corresponding to presence of lighting pertained to proportions of nighttime crashes. Even though the HSM provides default values of various nighttime crash proportions, it also recommends that default proportions of nighttime crashes should be replaced by jurisdiction-specific crash proportions in order to obtain more accurate crash estimations. These proportions were obtained for rural 4D and 4U highways in Kansas and compared with the HSM default values as shown in Table 5.

After applying CMFs, the final $N_{Predicted}$, or the number of predicted crash frequencies, was obtained for each rural divided and undivided segment. The sum of predicted crashes for all 281

4D segments was estimated to be 1,902, but the total number of actual observed crashes was 2,730. A calibration factor of 1.43 was obtained by dividing the total number of observed crashes by the total number of predicted crashes. A separate calibration factor was obtained for fatal and injury crashes. The total number of observed fatal and injury crashes on 4D segments was 528; predicted crashes from SPF were 1,008. Therefore, it yielded a calibration factor of 0.52. Detailed calculation of calibration factors are shown in Table 6.

Table 5: Proportions of Nighttime Crashes Obtained for Rural 4D and 4U Highways in Kansas

Roadway Type	Nighttime Crash Proportions	Kansas Four-lane Divided Highways	HM-Given Default
4D	P_{inr}	0.599	0.426
	P_{pnr}	0.124	0.323
	P_{nr}	0.876	0.677
4U	P_{inr}	0.533	0.255
	P_{pnr}	0.140	0.361
	P_{nr}	0.860	0.639

Note: P_{inr} = Proportion of nighttime crashes for unlighted segments that involved fatality or injury; P_{pnr} = Proportion of nighttime crashes for unlighted segments that involved PDO crashes; P_{nr} = Proportion of total crashes for unlighted segments that occurred at night.

Table 6: Calibration Factor Calculation of Four-Lane Divided Segments in Kansas

No. of Fatal Crashes	No. of Injury Crashes	Total (Fatal / Injury) Crashes	No. of Property Damage Crashes	Total (Fatal + Injury + Property Damage Only) Crashes	No. of Daytime Crashes	No. of Nighttime Crashes	Nighttime Fatal Crashes	Nighttime Injury Crashes	Nighttime PDO Crashes	No. of Total Nighttime Crashes	Predicted Total Crashes	Predicted Fatal / Injury Crashes
45	483	528	2202	2730	1087	1636	18	185	1433	1636	1902	1008

$$\text{Total Crash, } C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{2730}{1901.58} = 1.436$$

$$\text{Fatal and Injury Crash, } C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{528}{1007.69} = 0.524$$

The sum of predicted crashes for all 83 4U segments was 65.66, and the total number of observed actual crashes was 107. A calibration factor of 1.63 was obtained by dividing the total number of observed crashes by total predicted crashes. A separate calibration factor was obtained for fatal and injury crashes. There were 20 observed fatal and injury crashes on these segments; there were 41

predicted crashes from SPF. Therefore, it yielded a calibration factor of 0.49. Detailed calculation of calibration factors are shown in Table 7.

Table 7: Calibration Factor Calculation of Four-Lane Undivided Segments in Kansas

No. of Fatal Crashes	No. of Injury Crashes	Total (Fatal / Injury) Crashes	No. of Property Damage Crashes	Total (Fatal + Injury + Property Damage Only) Crashes	No. of Daytime Crashes	No. of Nighttime Crashes	Nighttime Fatal Crashes	Nighttime Injury Crashes	Nighttime PDO Crashes	No. of Total Nighttime Crashes	Predicted Total Crashes	Predicted Fatal / Injury Crashes
0	20	20	87	107	50	57	0	8	49	57	65.66	41.06

$$\text{Total Crash, } C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{107}{65.66} = 1.63$$

$$\text{Fatal and Injury Crash, } C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{20}{41.06} = 0.487$$

Calibration factors for total crashes on rural 4D and 4U segments were greater than 1.0 and it indicated that the HSM underpredicts crashes on rural multilane highways in Kansas. Therefore, multiplying the calibration factor by the prediction under base conditions lowers the predictions to match observed frequencies on average. However, the calibration factor for fatal and injury crashes on both 4D and 4U highway segments were less than 1.0, indicating overprediction by HSM; therefore, multiplying the factor increases the predictions to match observed frequencies. These calibration factors are unable to accurately predict crashes for rural highways in Kansas. Furthermore, the calibration factors contradict between total crashes and fatal and injury crashes. Rural multilane highways experienced fewer observed fatal and injury crashes compared with HSM predicted fatal and injury crashes, which resulted in such small calibration factors.

This overprediction or underprediction of crashes is caused by the observed crashes and the uncalibrated HSM predicted crashes. By applying this calibration factor, according to HSM recommendations, this overprediction or underprediction can be addressed at least partially. However, this research made an attempt to improve the crash prediction for rural multilane highways in Kansas without altering the HSM given SPF.

HSM Calibration – Four-lane Intersections

A total of 199 4ST intersections and 65 3ST intersections at minor approach were considered in the calibration for this study. Using the KDOT videologs, a total of 229 crashes were observed within an intersection-box for all 4ST intersections, and 53 crashes were observed within an intersection-box for all 3ST intersections. Using intersection-related crashes from the KCARS database, 112 and 17 intersection-related crashes were found for 4ST and 3ST intersections, respectively. Both sets of observed crashes were used to obtain two pairs of calibration factors. Figures 6 and 7 show crash distributions obtained through both methods for 4ST and 3ST intersections, respectively.

Figure 6: Distribution of Crash Frequency on 4ST Intersections

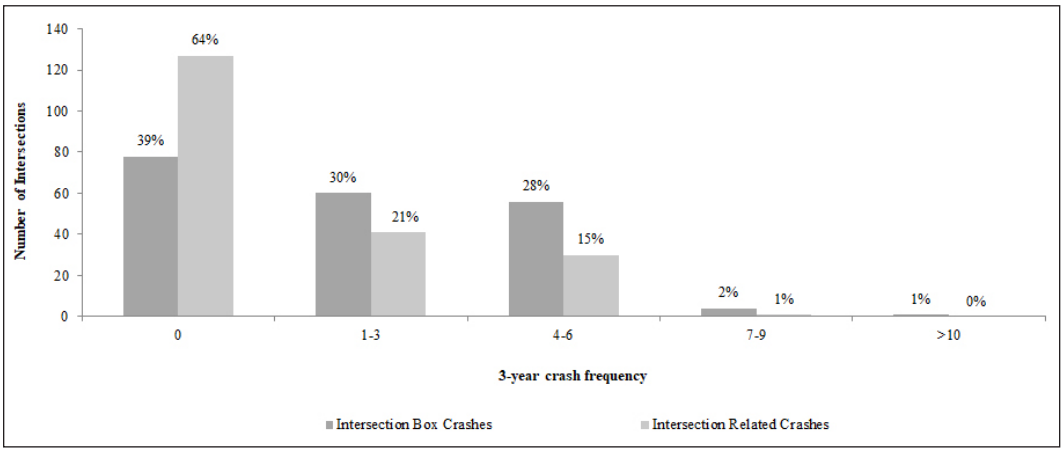
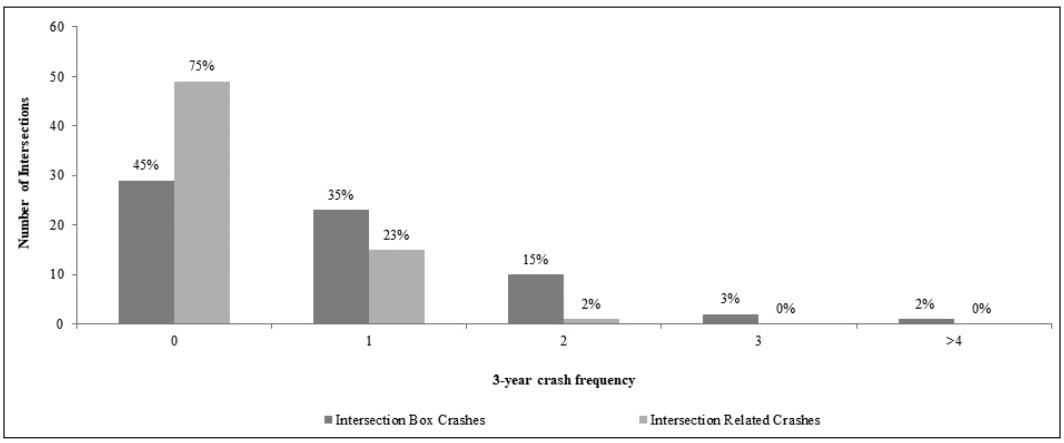


Figure 7: Distribution of Crash Frequency on 3ST Intersections



Descriptive statistics for 4ST and 3ST intersections are shown in Table 8. For 4ST intersections, the average major road traffic was 7,271 vpd and minor traffic volume was 990 vpd. Some intersections had minor traffic volumes as low as 40, but many intersections had high traffic volumes of 17,500 vpd. Intersection skew angles averaged 3.92 degrees since most of them were at exact right angles. Looking through the KDOT videologs, only 43 intersections contained right-turn lanes, and 30 intersections had lighting posts. The average number of crashes within an intersection-box was 1.15, with the number of crashes ranging from zero to 11. Intersection-related crashes from the KCARS database averaged 0.56 crashes, with the number of crashes ranging from zero to 5.

For 3ST intersections, the average major road traffic was 5,173 vpd and minor traffic volume was 544 vpd. Looking through the KDOT videologs, only seven intersections contained right turn lanes, and two intersections had lighting posts. The average number of crashes within an intersection-box was 0.81, with the number of crashes ranging between zero and 4. Intersection-related crashes from the KCARS database averaged 0.26 crashes, with the number of crashes ranging from zero to 2.

Table 8: Descriptive Statistics for Rural Four-Lane Intersections

Roadway Type	Description	Average	Minimum	Maximum	Std. Dev.
4ST	Major Road AADT (vpd)	7,271	490	17,500	4024
	Minor Road AADT (vpd)	990	40	5,650	1122
	Skew Angle (degrees)	3.92	0	60	12.98
	Presence of Right Turn lane on Major Road	0.21	0	1	0.41
	Presence of Lighting Post	0.15	0	1	0.36
	Number of Crashes within Intersection-box	1.15	0	11	1.43
	Number of Intersection-Related Crashes	0.56	0	5	0.88
3ST	Major Road AADT (vpd)	5,173	490	12,600	3,274
	Minor Road AADT (vpd)	544	20	2,780	543
	Skew Angle (degrees)	1.23	0	30	5.45
	Presence of Right Turn lane on Major Road	0.10	0	1	0.31
	Presence of Lighting Post	0.03	0	1	0.17
	Number of Crashes within Intersection-box	0.81	0	4	0.92
	Number of Intersection-Related Crashes	0.26	0	2	0.23

After obtaining the observed crash frequency, this study obtained the predicted number of crashes. HSM-SPF has two formats for intersection calibration, as previously shown in Equations 2 and 3. Since major and minor approach AADTs were available, Equation 2 was used to obtain predicted crashes at 4ST and 3ST intersections. Charts and equations in the HSM were used to obtain CMFs for intersection skew angle, presence of right-turn lane on major road, presence of left-turn lane on major road, and presence of lighting posts (AASHTO 2010).

CMF factors were obtained from Tables 11-22 and 11-23 and Equations 11-20, 11-21, and 11-22 of Chapter 11 of the HSM for intersection skew angles, left-turn lane on major road, right turn lane on major road, and the presence of lighting (AASHTO 2010). After applying the CMFs, final N_{spf} for each rural intersection was obtained, which was the number of predicted crashes. The summation of predicted crashes for all 199 4ST intersections was 252. Using intersection-box (method one), the total number of observed crashes within an intersection-box was 229. A calibration factor of 0.91 was obtained by dividing the total observed crashes by the total predicted crashes. Using method two, a calibration factor of 0.44 was obtained from the total observed 112 intersection-related crashes.[2] A separate calibration factor was obtained for fatal and injury crashes. Total observed fatal and injury crashes on these intersections were 99 from method one and 28 from method two. Calibration factors of 0.74 and 0.21 were obtained from method one and two, respectively, using Equation 6. Table 9 shows detailed calculations for calibration factors of 4ST intersections.

Table 9: Calculation of Calibration Factors for 4ST Intersections

Method of Obtaining Observed Crashes at Intersections	No. of Fatal Crashes	No. of Injury Crashes	Total (Fatal / Injury) Crashes	No. of Property Damage Crashes	Total (Fatal + Injury + Personal Damage Only)	No. of Daytime Crashes	No. of Nighttime Crashes	Nighttime Fatal Crash	Nighttime Injury Crash	Nighttime PDO Crash	No. of Total Nighttime Crashes	Predicted Total Crashes	Predicted Fatal / Injury Crashes
1	3	96	99	130	229	62	167	2	17	148	167	252.13	134.67
2	0	28	28	84	112	37	75	0	21	54	75		

Intersection-box (Method 1),

Total Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{229}{252.13} = 0.91$

Fatal and Injury Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{99}{134.67} = 0.74$

Intersection-related crashes (Method 2),

Total Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{112}{252.13} = 0.44$

Fatal and Injury Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{28}{134.67} = 0.21$

After applying the CMFs, final Nspf for each rural intersection was obtained, which was the number of predicted crashes. The summation of predicted crashes for all 65 3ST intersections was 18.44. Using intersection-box (method one), the total number of observed crashes within an intersection-box was 53. A calibration factor of 2.87 was obtained by dividing the total observed crashes by the total predicted crashes. Using method two, a calibration factor of 0.92 was obtained for the 17 observed intersection-related crashes. A separate calibration factor was obtained for fatal and injury crashes. Total observed fatal and injury crashes on these intersections were 10 from method one and 4 from method two. Calibration factors of 1.16 and 0.47 were obtained from method one and two, respectively, using Equation 6. Table 10 details calibration factors for 3ST intersections.

Using observed crashes within an intersection-box (method one), the obtained 0.91 calibration factor for total crashes on rural 4ST intersections indicated precise crash prediction. The HSM underpredicts total crashes on 3ST intersections when considering crashes from method one but showed more precise prediction when considering intersection-related crashes (method two). Fatal and injury crash prediction followed a similar trend for both methods of observed crashes. Results indicated that, using intersection-boxes (method one), the HSM accurately predicts fatal and injury crashes when compared with actual observed crashes on rural 4ST and 3ST intersections.

Table 10: Calculation of Calibration Factors for 3ST Intersections

Method of Obtaining Observed Crashes at Intersections	No. of Fatal Crashes	No. of Injury Crashes	Total (Fatal / Injury) Crashes	No. of Property Damage Crashes	Total (Fatal + Injury + Personal Damage Only)	No. of Daytime Crashes	No. of Nighttime Crashes	Nighttime Fatal Crash	Nighttime Injury Crash	Nighttime PDO Crash	No. of Total Nighttime Crashes	Predicted Total Crashes	Predicted Fatal / Injury Crashes
1	0	10	10	43	53	15	38	0	7	31	38	18.44	8.59
2	0	4	4	13	17	8	9	0	1	8	9		
Intersection-box (Method 1), Total Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{53}{18.44} = 2.87$ Fatal and Injury Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{10}{8.59} = 1.16$													
Intersection-related crashes (Method 2), Total Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{17}{18.44} = 0.92$ Fatal and Injury Crash, $C_r = \frac{\text{Total Observed Crashes}}{\text{Total Predicted Crashes}} = \frac{4}{8.59} = 0.47$													

Modification of HSM-Given SPF

Results obtained from the calibration process showed that the HSM methodology underpredicts total crashes on rural multilane highways in Kansas. Furthermore, fatal and injury crashes were overpredicted by the HSM methodology. Therefore, modification of existing SPF is necessary for application to rural Kansas.

The HSM provides guidance pertaining to SPF modification for a state with available local data. Specifically, Appendix A of Part C in the HSM describes the three outlined components. FHWA has funded efforts to develop such guidance (Srinivasan et al. 2013). In order to increase the accuracy of results of the HSM procedures, states have been encouraged to customize the procedures with local data (AASHTO 2010). One way to allow the HSM procedure to more accurately reflect local conditions is to develop calibration factors that would be applied to the default SPFs in the HSM. However, optimum HSM customization for each state requires consideration of factors such as availability of data and resources. Therefore, this paper identified a methodology to customize the HSM for Kansas as accurately as its resources allow.

Customization of the HSM is possible through a combination of the three components: SPF, CMF, and calibration factor. For example, the HSM can be customized with calibration factors calculated using local data, default SPFs, and crash proportions, which may be the typical method so states that lack available data and resources can develop individualized SPFs. However, many other methods can be used to customize the HSM by combining the three components. Although

these methods are not explicitly described in the predictive methods of HSM, they can be inferred from Appendix A and relevant references. Dixon et al. (2012) explored several options related to calibration factors and crash proportions under default SPFs given in the HSM. In this study, development of new regression coefficients for existing HSM-given SPFs was utilized and executed.

Since the HSM models were calibrated using the whole rural 4D and 4U dataset, it is fair to do the same with the modified SPF. Otherwise, both methods would not be treated in the same way. Currently, while developing new Kansas-specific SPFs, two separate datasets were used for model development and model validation of these new SPFs. However, that is not part of this manuscript.

As shown in Equation 1, the SPF considers segment length and AADT as independent variables, considering *a* as the intercept of the model and *b* as the parameter estimate for AADT. The original SPF given in the HSM indicated 1.0 as the coefficient for segment length in the model.[3] However, while using Kansas-specific data, new coefficient *p*, corresponding to segment length, was considered for the model as given in Equation 7.

(7) $N_{SPF=e^{[a+b\times\ln(AADT)+p\times\ln(L)]}}$

where, N_{SPF} is the base total expected average crash frequency for the rural segment, *AADT* is the average annual daily traffic on the highway segment, *L* is the length of the highway segment (miles), and *a, b*, and *p* are the regression coefficients.

In order to perform this task, data from the existing set of segments were used to run a Negative Binomial Regression model.[4] Separate models were run for 4D and 4U segments. Table 11 compares regression coefficients given in Chapter 11 of the HSM for both segments with coefficients obtained based on Kansas-specific data. R^2 for the 4D and 4U models were found to be 0.89 and 0.82 for total crashes and 0.81 and 0.72 for fatal and injury crashes, respectively.

Parameter estimates of 4D and 4U differed significantly at all three severity levels. The t-test was used to determine if slope coefficients obtained for Kansas segment data differed from default values at the 0.05 significance level. All coefficients for 4D were found to be numerically different. From t-test results, Kansas's SPFs were determined to be statistically significantly different from the corresponding default HSM-given SPFs.

Table 11: Comparison of Regression Coefficients

Severity Level	Default HSM Coefficients		Kansas-Specific Coefficients (t-statistics)		
	a	b	a	b	p
4D					
Total Crashes	-9.025	1.049	-6.317 (2.034)	0.795 (1.532)	0.898
Fatal and Injury Crashes	-8.837	0.958	-10.030 (4.923)	1.059 (2.763)	0.399
4U					
Total Crashes	-9.653	1.176	-6.347 (3.332)	0.822 (1.923)	0.912
Fatal and Injury Crashes	-9.410	1.094	-8.206 (4.287)	0.817 (2.174)	0.747

Afterward, the newly obtained regression coefficients were used to obtain predicted crashes at each 4D and 4U segment, followed by acquisition of the calibration factor for each facility type. Calculated calibration factors for 4D facilities were close to 1.0, as shown in Table 12; however, a calibration factor of 0.858 was obtained for total and injury crashes on rural 4U segments. This

calibration factor was less than the usual acceptance limit.[5] A calibration factor close to 1.0 indicates that the SPF accurately predicts crash frequency for the facility type and matches the local conditions. Therefore, it is evident that by modification of the SPF with Kansas-specific regression coefficients improved the prediction of crash frequency on rural 4D roadway segments in Kansas.

However, further research must be conducted on 4U segments in order to achieve a calibration factor within an acceptable limit, especially for fatal and injury crashes. Small sample size is the biggest challenge for 4U segments. HSM suggests having at least 30-50 segments in the sample for reliable estimation. Also including additional explanatory variables in the new regression model could provide satisfactory results. Currently we are developing Kansas-specific SPFs to discover whether they can predict crashes with increased level of accuracy.

Table 12: New Calibration Factors Using the Modified SPF

Facility Type	Severity	Calibration Factor
4D	Total Crashes	0.956
	Fatal and Injury Crashes	1.002
4U	Total Crashes	1.019
	Fatal and Injury Crashes	0.858

CONCLUSIONS

Prior to this study, KDOT was able to apply the rural two-lane model from the HSM because a study had been completed to calibrate such facilities (Lubliner and Schrock 2012). However, when the analysis of a multilane facility was requested, it could not have been completed without calibration. Therefore, an acceptable method to predict crashes for rural multilane highway segments and intersections in Kansas must be identified or developed. This study calibrated rural four-lane divided and undivided highways in Kansas using SPFs described in the HSM. Crash data for years 2011 to 2013 were used to obtain observed crash frequencies, and predicted crash frequencies were obtained using SPFs in the HSM, which were further modified by multiplying by CMFs.

Results obtained from the calibration process showed calibration factors of 1.43 and 1.63 for 4D and 4U segments, respectively. Therefore, it was seen that the HSM methodology underpredicts total crashes on rural multilane highways in Kansas. These calibration factors are unable to accurately predict crashes for rural highways in Kansas. Furthermore, calibration factors for fatal and injury crashes were found to be 0.52 and 0.49 for 4D and 4U segments, respectively, thereby indicating an overprediction of fatal and injury crashes. Rural multilane highways experienced fewer number of observed fatal and injury crashes compared with HSM predicted fatal and injury crashes, which resulted in such small calibration factors.

Crash proportions based on severity, daytime to nighttime crash, and collision type indicated a significant difference compared with the default crash proportion mentioned in the HSM. An approach of modifying the HSM-given SPF regression coefficients was taken to observe variation in the crash prediction. Since the HSM models were calibrated using the whole rural 4D and 4U dataset, the same data were used for the modified SPF. Predicted crash frequency was obtained by using the SPFs with new coefficients, which was further modified by multiplying by the CMFs. The final calibration factors for both 4D and 4U facilities indicate significant improvement in terms of crash prediction for rural Kansas. Therefore, using the modified SPF for multilane highways in Kansas total crashes and fatal and injury crashes can be more accurately predicted compared with using only HSM methodology.

In addition to segments, this study calibrated multilane intersections. The HSM methodology was followed to obtain the number of predicted crashes at 4ST and 3ST intersections. Observed crashes at intersections were considered using two methods: intersection-boxes and intersection-related crashes. This study found that intersection-box crashes (method one) is predicting the fatal and injury crashes comparatively close to actual observed crashes on rural 4ST and 3ST intersections.

The results obtained from this study have enlightened new paths for proceeding with the crash predictions for rural Kansas. The next phase of this research is currently addressing development of Kansas-specific SPFs for rural multilane segments. By considering several additional variables in the new SPF, their applicability in increasing the accuracy of crash prediction will be verified. Finally, the HSM calibrated models will be compared to the new SPFs and modified HSM given SPFs to determine the best option for the most accurate crash predictions of rural multilane highway segments in Kansas.

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Endnotes

1. These methods have not been used in any previous study. Intersection data for Kansas were not available at the time of this study. Therefore, both methods were used to find out whether there is any difference in results.

2. The intersection–related crashes were extracted from the KCARS database, which was designated while entering into the crash record. On the other hand, intersection box crashes were counted based on the coordinates of the crash location, where the level of accuracy of number of crashes is higher.

3. The original SPF given in HSM was developed by AASHTO where 1.0 was the coefficient value of segment length.

4. Negative binomial model was used because it is most commonly used for developing a crash prediction model.

5. A calibration factor close to 1.0 indicates that the SPF accurately predicts crash frequency for the facility type and matches the local conditions. Usually if the factor is within 0.9-1.1, then it is considered to be within the acceptance limit.

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Indian Vehicle Ownership: Insights from Literature Review, Expert Interviews, and State-Level Model

by Prateek Bansal and Kara M. Kockelman

This study reviews existing vehicle ownership models for India and describes the results of nine experts' interviews to gather insights about Indians' travel patterns and vehicle choices. According to the experts, vehicle price, fuel economy, and brand (in declining importance) are the most decisive factors in Indians' car purchase choices. This study also estimated household vehicle ownership levels across India's 35 states using Census 2011 data. The results suggest that states with a higher proportion of computer-owning households and higher share of households living in rural areas with larger household size, ceteris paribus, are likely to have higher car ownership.

INTRODUCTION

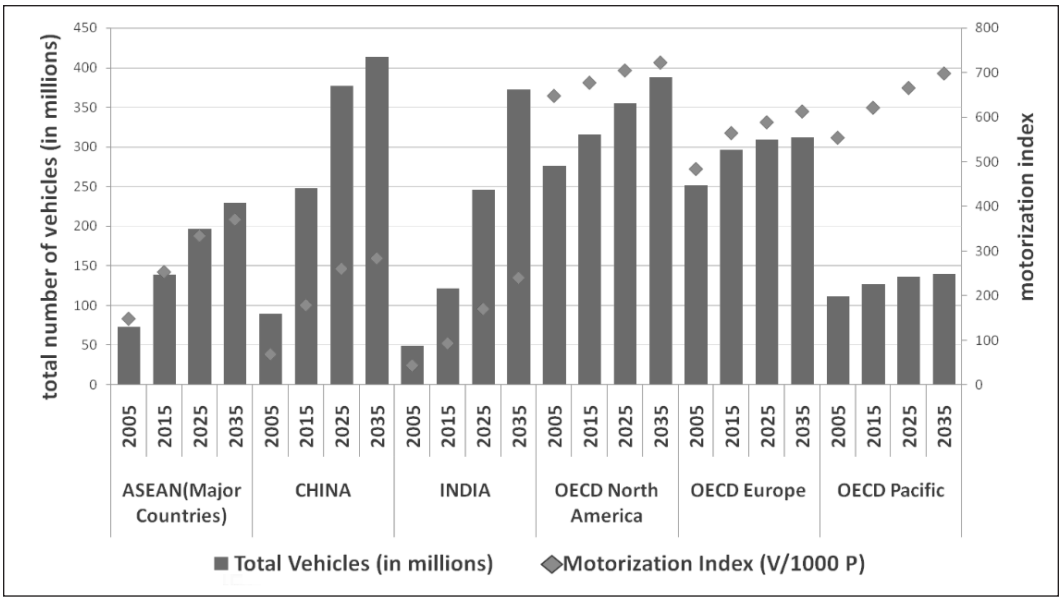
Over the past few decades, India has experienced rapid urbanization on a large scale. The subsequent increase in transport demand, hampered by resource constraints and limited capacity, has deepened the divide between demand and transport supply (Srinivasan et al. 2007). The heavily strained transit systems have provoked a shift toward private vehicles, thereby worsening traffic jams, safety concerns, and gridlock on dense urban streets (Pucher et al. 2005). The primary problem is not the increase in number of vehicles but rather their high concentration in a few densely populated metropolitan areas. In 2001, 32% of all vehicles were in such cities though these places constitute only 11% of India's urban population (Ministry of Urban Development 2008).

Using data from the Ministry of Road Transport and Highways, Dash et al. (2013) calculated car ownership rates in India. From 2001 to 2009, ownership levels of four-wheelers (cars, jeeps, and taxis) nearly doubled from 6.59 such vehicles per 1,000 people to 12.68. The rapid growth of vehicle acquisition rates has raised concerns about social, economic, and environmental sustainability (Chamon et al. 2008). At the same time, the growth symbolizes the desire of India's middle-class to lead more comfortable lives (Shirgaokar et al. 2012) and engage in more economic and discretionary activities. For a highly populated (1.28 billion persons) and developing country like India (the world's fourth largest importer of petroleum after the United States, China, and Japan), understanding the factors that determine consumer behavior relating to private vehicle purchases and initiating policies for the sustainable evolution of transportation system are essential (Dash et al. 2013).

As compared with aggregate models of vehicle ownership (at zone, city, or state levels), disaggregate models (at individual or household levels) better explain the behavioral relationships between demographics and other attributes and their vehicle ownership (Kumar and Krishna Rao 2006). However, due to the scarcity of disaggregate data in India, relatively few studies have developed such models (Dash et al. 2013). Additionally, culture variations, travel patterns, and mobility needs do not allow developing countries like India to adopt model specifics and parameters established in developed countries. For example, in contrast to developed countries, India has a very high share (around 75%) of two-wheelers (vs. passenger vehicles). Figure 1 suggests that while developed countries' vehicle ownership and motorization levels are relatively saturated, they are rising rapidly in developing countries like India and China (Embarq India 2012)[1]. Moreover, India's heterogeneous traffic flow conditions, with all vehicle types sharing roads with almost no lane discipline, offer a major contrast to the strict lane regulations found in nearly all developed countries. Relatively low per-capita incomes also make car ownership a symbol of luxury and

status. In the absence of widespread and behaviorally-sound disaggregate models and recognizing issues in adopting models developed for other countries, planners and automobile manufacturers from developing countries like India have to look at aggregate measures (e.g., growth rates) or prioritization heuristics to make policy investment decisions (Dissanayake and Morikawa 2002).

Figure 1: Number of Vehicles and Motorization Rates by Region



Source: Embarq India (2012); V/1000 P = vehicles per 1,000 person

This study provides a comprehensive review of disaggregate-level research studies that investigate the effects of demographic and built environment characteristics on vehicle ownership rates across India. It is important that researchers, policymakers, and automobile manufacturers appreciate the limitations of existing vehicle ownership models and the need for new models in an Indian context. Indian travel choice experts were also interviewed (via a detailed email questionnaire), and those findings are summarized here to provide further insights about current and future vehicle ownership choices in India (e.g., two-wheelers vs. four-wheelers, used vs. new vehicles, conventional vs. electric cars, and compact cars vs. sport utility vehicles [SUVs]). Experts' perspectives on different policy and practice scenarios (e.g., better enforcement of safety laws and improvements in travelers' lane-keeping), prospects for car-sharing programs, barriers to and policies for electric vehicle sales, and Indians' fuel type usage are also summarized here.

Research personnel at many key Indian institutions were contacted, confirming that household travel survey data cannot be readily obtained for Indian cities. In the absence of such data, this study estimated household two-wheeler (scooters, motorcycles, and mopeds) and four-wheeler (cars, jeeps, and taxis) ownership levels for all states across India using least-squares regression techniques, with as many explanatory variables as one can find at this level of aggregation, as presented in this article.

This paper has three major contributions: Providing a detailed review of existing studies estimating Indian vehicle ownership rates, obtaining experts' opinions on Indians' vehicle ownership decisions and related choices, and estimating vehicle ownership rates across India (for motorized two-wheelers and four-wheelers/cars).

DISAGGREGATE VEHICLE OWNERSHIP MODELS FOR INDIA

Vehicle ownership models can be used to develop policies affecting congestion, infrastructure, emissions, equity, and safety. They help anticipate the most plausible effects before a policy is instituted. Banerjee (2011) sheds light on such outcomes in her study of city of Surat. For example, increasing the two-wheeler's price is expected to significantly diminish the mobility of low-income households in India, causing social inequity issues. Instead, policies that encourage two-wheeler ownership, may be useful in India because such vehicles are relatively spaced and fuel-efficient, but safety aspects need further investigation (Banerjee 2011).

In the Indian context, it is important to understand the factors affecting two-wheeler ownership-not just because of their high usage levels, but also due to their distinct impacts on system performance measures, such as parking, congestion, energy consumption, and air quality. This article separately reviews studies examining only car-ownership models and those having both car and two-wheeler ownership models. Table 1 summarizes the data, response variables, and choice models used in all past disaggregate vehicle ownership models developed for India.

Car Ownership Models

Kumar and Krishna Rao (2006) conducted a stated and revealed preference study for the Mumbai Metropolitan Region of Maharashtra and developed a multinomial logit (MNL) car ownership model (alternatives considered 0, 1, and 2 cars). The SP (standard preference) experiment's results suggest a very high unwillingness of Indians to share their home addresses and incomes, a key reason behind the relatively low response rate of 17.3%[2]. They found car ownership rises with household income and falls with car prices, family size, and home ownership, ceteris paribus. Respondents were interested in owning a car for recreational and shopping trips rather than for work commutes. After comparing the results of their stated and revealed preference data, the authors concluded that stated preference approaches appear to be successful in modeling vehicle ownership decisions of households in India.

Chamon et al. (2008) used 29,631 Indian households' expenditure data in 2004, across urban and rural areas. It appears they used expenditures as a proxy for income, but they did not reveal any further details and estimated a binary probit model with two alternatives: own at least one car vs. own no cars. Based on their probit model results, they projected[3] that 11% and 34% of Indian households will own at least one car in 2030 and 2050, respectively. Additional details about their model results were not provided.

Car and Two-Wheeler Ownership Models

Srinivasan et al. (2007) and Gopisetty and Srinivasan (2013) used Chennai Household Travel Survey data (collected between December 2004 and May 2005) to understand car and two-wheeler ownership. While both studies used the same datasets, the first focused on understanding demographic, mobility-related, and land use factors affecting vehicle ownership increases over five years using two separate ordered probit models, and the latter study accounted for simultaneity[4] in two-wheeler and car ownership levels, as well as trip frequencies and vehicle ownership levels using a three-stage least squares (3SLS) model.

Srinivasan et al. (2007) found that two-wheeler and car ownership rise with household income; and the latter is also positively affected by lagged-income. Having a credit card in one's name was controlled for (as an explanatory variable) and it positively affected car (but not two-wheeler) ownership, most likely due to the holder's access to loans and other financing options. The number of household workers positively affected two-wheeler ownership, but had no direct effect on car ownership (although such effects are also picked up through the presence of the income and income-

related variables). Consistent with Dash et al.'s (2013) findings, households with more children (below five years of age) were more likely to own a car, presumably due to safety concerns and the importance of meeting their relatively complex travel needs. Households with female drivers were also more inclined to buy a car. As the average work distance of all household workers increased, the propensity to purchase two-wheelers rose, while the tendency to purchase four-wheelers fell, perhaps due to two-wheeler's higher fuel economy. Households noting more frequent maintenance ("personal-business trips") activities (e.g., visiting a doctor) and respondents in urban areas tended to purchase two-wheelers. This could be due to congestion and parking issues. Home ownership also increased the car-ownership probability. Of course, both home ownership and vehicle ownership are major economic and social status symbols in India, so wealthy households with cars generally own a home and vice versa (though this home-ownership effect is in some conflict with Kumar and Rao's [2006] statistical result). It is surprising that accessibility to buses/transit was predicted to have no effect on trip frequencies or vehicle ownership levels. Households with a grocery store nearby (within 500 meters) were estimated to be less likely to acquire cars, as compared with other households. Cell phones and peer pressure positively influenced vehicle ownership in general. However, if local vehicle ownership of two-wheelers was substantial (more than seven of every 10 households in the neighborhood), car ownership fell. Additionally, households without cars were found to have the greatest inclination towards buying a car. Since 70% of households surveyed did not have a car at the time of the survey (2004-05), the authors expected a rapid increase in car ownership, due to rising incomes.

Gopisetty and Srinivasan's (2013) results with those same data indicate a rise in car ownership with the number of college graduates in the household, reflecting greater car affordability, presumably greater need, and perhaps a higher value placed on comfort. Respondents living in urban areas indicated a higher propensity to buy two-wheelers, but not cars, perhaps due to congested roadways and limited parking availability. Moreover, poor road surface conditions appeared to motivate two-wheeler purchases over four-wheeler purchases, presumably due to more affordable vehicle maintenance costs. Additional results related to endogeneity suggest that trip frequency has a negative effect on car ownership, but not on two-wheeler ownership, perhaps because frequent trip-makers face higher operating cost of cars and more often encounter congestion and parking issues. Surprisingly, two-wheeler ownership was estimated to be negatively associated with trip frequencies, perhaps due to more efficient trip making by two-wheelers.

Banerjee et al. (2010) conducted a survey in Surat, a typical city in western India, to analyze their choices across new and used motorized two-wheelers and cars, and across different car-size segments. This is the only study in an Indian context that explains the factors affecting the choice of new versus used vehicles, as well as the size categories of these choices. Banerjee et al. (2010) used an MNL model with 18 vehicle choices (both new and used options for two-wheelers and eight car-size segments). Their results suggest that small cars are preferred in general, but compact cars and SUVs are the most popular. They inferred that consumers do not want larger cars (like SUVs) due to congestion and parking issues in India; however, Indians still prefer them, and not because of their higher seating capacity, but rather due to their symbolic status. This finding supports a market potential for small luxury cars in India. Nonetheless, more interior space in larger vehicles was attractive for the bigger households. Furthermore, the study found that consumers' choices are highly sensitive to operating costs, as compared to vehicle purchase price. For this reason, respondents stated that new vehicles were preferred over used ones. Banerjee et al. also explored the effect of attitudes and perceptions on consumer choices. They concluded that the cost and utility of a vehicle surpass the importance of perception biases, such as status symbolism. Their findings undermine the importance of advertising in influencing purchasing decisions. Other qualitative results of their survey suggest that an individual's vehicle choice is highly influenced by peer experiences of and peer reports on a vehicle as opposed to his or her own experiences and research. And the most expensive vehicle in an Indian household is generally used by highest income earner or the oldest

male member of the household. Apart from a vehicle's price and operating costs, availability and cost of spare parts was given as an important factor in vehicle type choice.

Padmini and Dhingra (2010) developed MNL models to estimate car and two-wheeler ownership levels for residents of the Pune metropolitan area using revealed-preference, home-interview survey data. They also investigated the respondents' willingness to shift their mode choice from a private vehicle they already owned to the region's metro (subway) system. Padmini and Dhingra (2010) used prediction success tables to check the models' goodness of fit.

Shirgaokar et al. (2012) also used MNL models to understand how various factors (like home and work locations, socio-economic variables, and trip characteristics) influence the middle-class's purchases of cars (including jeeps and taxis) and motorized two-wheelers. They used household travel survey data, collected by the Mumbai Metropolitan Regional Development Agency (MMRDA) in the Greater Mumbai Region (GMR), and concluded that better transit services would reduce the need for vehicle ownership that Indians feel. They found that vehicle ownership utilities increase when the household head is married and decrease when he/she makes longer-distance trips (especially for two-wheeler ownership, due to congestion and safety concerns). A preference for a car (over a two-wheeler) is stronger in the presence of children (under age 5), a college-educated primary wage earner, higher per-capita income, larger household size, and bigger house ownership. A preference for two-wheelers (over cars) is stronger when the primary wage earner is male and travels more often. Specifically, younger people are estimated to prefer two-wheelers, while older Indians are more inclined toward cars, perhaps due to an increase in purchasing power and change in perception about safety and comfort with one's age. Car ownership tended to fall for those living on the urban periphery with high job densities at their work locations, ceteris paribus. This pattern reversed for two-wheeler ownership. Car owners living in urban cores, but working in suburbs, and two-wheeler owners living and working in the suburbs, were both estimated to derive higher vehicle utility. This implies that cordon pricing may help contain India's car market, but not its two-wheeler market.

Dash et al. (2013) developed a disaggregate model for private vehicle ownership using India's Consumer Expenditure Survey data collected by the Nation Survey Sample Office (NSSO) from July 2009 to June 2010. Due to the high likelihood of erroneous income data[5] in developing countries, the study used household *expenditures* as proxy for income and economic standing. Similar to Chamon et al. (2008), theirs was a nationwide vehicle ownership model. Dash et al. (2013) considered the following four vehicle choices in their MNL model: no motorized private vehicle, only two-wheelers, only cars, both two-wheelers and cars in the household. They found that per-capita expenditures, the presence of children, and household size all have a positive association with two-wheeler and car ownership. Rural households are more inclined to own cars than are urban households, provided they can afford one, thanks to their longer travel distances, better parking options (more unused land), and less frequent transit options. As expected, the presence of young adults (18 to 35 years) increased the probability of households owning two-wheelers only. They may have obtained better insights if their data included vehicle make and model, number of vehicles owned, fuel type of vehicles owned, distances traveled by each vehicle owned, and average time spent traveling by each household member.

This exhaustive review of the literature suggests that Indian vehicle ownership models exist for the regions of Mumbai, Chennai, Pune, and Surat. Surprisingly, however, there appears to be no individual- or household-level vehicle ownership models available or publicly accessible for key metropolitan areas like Delhi (India's capital city), Bangalore (India's "Silicon Valley"), and Kolkata (India's third most-populous metro area). Hence, there is a need to develop vehicle ownership, vehicle preference, and vehicle use models at least for key Indian cities.

Table 1: Summary of Past Disaggregate Vehicle Ownership Models for India

Previous Studies	Data Description	Sample Size	Response Variables	Choice Model
Kumar & Krishna Rao (2006)	Stated & reveled preference surveys in **Mumbai** Metropolitan Region (MMR) (2004-2005)	357 & 923 households in stated & reveled preference surveys, respectively	Car ownership (0, 1, or 2 cars)	MNL model
Srinivasan et al. (2007)	**Chennai** Household Travel Survey data (December 2004 – May 2005)	1,200 households	Increase in household's car and two-wheeler ownership over 5 years	Ordered probit model (OP)
Chamon et al. (2008)	**All India** consumer expenditure data, National Sample Survey Office, Govt. of India (2004)	29,631 households	Car ownership (own a car or not?)	Binary probit model (BP)
Banerjee et al. (2010)	Travel survey of households in **Surat** (Gujrat 2009)	128 households that had acquired new or used vehicles after April 2009, & 68 households that did not	18 vehicle classes (new & used two-wheelers, plus 8 car's size segments)	MNL model
Padmini & Dhingra (2010)	Home Interview Survey (revealed preference) data of **Pune** (2008)	3000 households	Car & two-wheeler ownership	MNL model
Shirgaokar et al. (2012)	Household travel survey for Greater **Mumbai** Region (GMR), collected by Mumbai's Metropolitan Regional Development Agency (2005-2006)	65,992 households across 35 urban areas plus 1,200 villages. 1.5% sample of the total population within the GMR	Three vehicle choice (no vehicle, only two-wheelers, & at least one car)	MNL model
Dash et al. (2013)	**All India** consumer expenditure data, National Sample Survey Office, Govt. of India (2009-10)	89,503 households	Household's car & two-wheeler ownership in single model	MNL model
Gopisetty & Srinivasan (2013)	**Chennai** Household Travel Survey data (December 2004 – May 2005)	1,200 households	Joint estimation of household's car and two-wheeler ownership, & trip frequency	Three-stage least squares (3SLS)

INSIGHTS FROM EXPERT INTERVIEWS

In total, 38 Indian travel choice experts were contacted in September 2014, and nine of them responded to the interview questionnaire[6]. Among these nine, five had obtained doctoral degrees in transportation engineering (three are professors and the other two are post-doctoral fellows), and the remaining four experts had obtained master's degrees and were working in leading travel demand modeling firms. The following subsections summarize the insights gathered from these expert interviews. These run the gamut from vehicle ownership and fueling decisions to used and electric vehicles, as well as suggestions for future research.

Factors Affecting Purchases of Cars and Two-Wheelers

According to the experts, key car-ownership advantages for Indians include a perception of greater safety (from traffic accidents and crime en route), social status, and comfort, with key concerns being parking availability and roadway congestion. Indians mainly consider price, fuel economy,

and brand (in decreasing order of importance) when making car-purchase decisions (across makes and models). For instance, all nine respondents ranked price as the number one criterion, and seven ranked fuel economy second. According to the experts, brand consciousness rises with household income. High-income households prefer costlier brands, like Mercedes or BMW; middle-income households prefer Japanese cars with good resale value (e.g., Toyota and Honda); whereas lower-middle income households prefer the relatively affordable brands (e.g., Maruti Suzuki). Compact cars are the most common vehicle-body choice in India due to ease of maneuvering and parking. Since overloading vehicles is a regular issue (i.e., multiple children are placed on two-wheeled and three-wheeled motorized vehicles, along with their adult riders), the presence of children in a household is not yet a big factor in determining car type purchased. Across the SUV spectrum, vehicles manufactured by Mahindra and Mahindra are most popular. More recently, families and companies offering transport for their employees have shown high interest in SUVs. Experts also think that individual preferences for car type are changing rapidly thanks to recent increases in purchasing power. A lower-priced and fuel-efficient SUV can cause a shift away from compact car purchases because SUVs are quite useful when driving from small towns and rural areas into big cities (sometimes offering an alternative to public transit for many workers' combined commutes). In terms of two-wheeler purchases, experts note that Indians rank fuel economy, price, engine power, and brand as top features (in decreasing order). Moreover, younger males prefer two-wheelers with more engine power, but typically do not want to pay more than they do for conventional two-wheelers.

Fuel Choices

As with Indians' vehicle purchases, price is a key determinant in fuel choice. Historically, diesel has been less expensive than gasoline in India because the national government subsidizes diesel to aid low-income taxicab and three-wheeler operators (both vehicles run on diesel). Gasoline is the most used fuel type in India, but long-distance travelers prefer diesel to reduce operating costs. The gap between gasoline and diesel prices has been narrowing since January 2013, when the government announced a very modest monthly increase of $0.008 (0.5 rupees) per liter in diesel prices to reduce oil companies' losses. Likely due to this factor, the share of diesel vehicles fell to 53% in 2013-14, from a peak of 58% reached in the prior year (The Economic Times 2014). An expert also endorsed the preference shift toward gasoline due to this deregulation of diesel price.

India's Electric Vehicle (EV) Market

Higher purchase costs, poor charging infrastructure availability, and lack of consumer awareness about the benefits of EVs are the major hurdles for EV penetration in India according to the experts surveyed. India's earlier fleets of EVs had maintenance issues, which needs to be addressed before significant adoption is expected by experts. To encourage EV adoption, the Indian government may pursue the following initiatives: provide subsidies and tax incentives for EV purchase, sublease EVs at competitive rates for short-term use, lower electricity costs for EV charging during off-peak hours, partner with businesses to provide charging infrastructure at workplaces and/or major parking stations, and provide a means of recycling the outdated vehicles as the technology improves.

Some of these strategies have already been implemented in India. In 2010 and 2011, the Government of India reduced the EV excise duty from 8% to 4%. Delhi, Rajasthan, Uttarakhand, and Lakshadweep states do not levy value-added tax (VAT) on EVs. In fact, the Delhi Government provides the highest incentives for EVs, with tax rebates amounting to 29.5% of the cost (Finpro 2013). Major manufacturer Mahindra Reva introduced plans, like battery leasing and exchange of petrol-fueled vehicles, with its Reva-i electric cars in Bangalore. In spite of these endeavors, the current Indian vehicle fleet comprises only about 0.4 million electric two-wheelers and a few

thousand electric cars (Daniels 2014). As suggested by experts, we investigated the National Electric Mobility Mission Plan (NEMMP), which suggests that government and industry players plan to invest over 230 billion rupees ($4B USD) to create a market for 5 to 7 million EVs (3.5 to 5 million pure electric two-wheelers, 1.3-1.4 million hybrid electric four-wheelers, and 0.2-0.4 million pure electric four-wheelers) by 2020, resulting in annual fuel savings of 677-769 million gallons (Ministry of Heavy Industry 2013).

The Market for Used Vehicles

According to one expert, maintenance costs are relatively low for vehicles in India, as compared with labor and parts costs in more industrialized countries. This feature, along with less economic ability to purchase new vehicles, causes consumers to hold their cars and two-wheelers longer. Related to this, an expert suggested that the International Journal of Hydrogen Energy estimated the average service life of a passenger car in India to be about 20 years (versus 16 years in the U.S.), with 9,300 miles of annual travel (which is similar to average annual U.S. use). According to cartoq.com, an average diesel car engine lasts 248,000 miles in India, whereas an average gasoline car engine lasts just 124,000 miles (versus an average light-duty vehicle lifetime of about 160,000 miles in the U.S.). However, there is a growing set of consumers with greater purchasing power who aspire to own the latest models, leading to a larger pool of used cars. India's used car market is becoming more formal and organized, but it may take another five to 10 years to catch up to U.S. conditions. Used cars often go to persons in one of three groups: 1) first-time car buyers from lower- and middle-income classes who cannot afford a new car, 2) new drivers who are not very confident in their driving, and 3) taxi companies. Whereas, two-wheelers are generally handed down to children before they are sold off and thus kept much longer than cars. If the used car market becomes increasingly organized and prevalent, Indians' propensity to purchase used cars over new two-wheelers may increase, since used cars are likely to be affordable for someone who had been planning to buy a new two-wheeler.

Safety Laws

One safety expert suggested that overloaded informal modes (e.g., jitney vans with capacity for eight actually carrying 15 persons), which transport children to and from school, have a good safety record. It will be interesting to study the mobility needs that are met by overloaded trains, buses, cars, two-wheelers, and three-wheelers in India. With improvements in vehicle technologies, experts expect airbags, anti-lock braking systems, and electronic stability control systems to become mandatory on new car sales in India before long. They noted that India's new *Transport and Safety Act* (Ministry of Road Transport and Highways 2014) has various safety law amendments. For example, front and rear seat belts are now required in all new cars sold, roadworthiness tests will be conducted for all cars and two-wheelers every five years, posted speed limits will be required on all streets, penalties will soon exist for hand-held mobile-device use, and a unified driver licensing system will be in place, among other policies. It is hoped that such policies will provide many valuable safety benefits to Indians.

Top Strategies for Foreign Manufacturers in India

The questionnaire also asked for recommendations for major manufacturers from developed countries. Many hope to increase car sales in India, and experts believe they should emphasize highly fuel-efficient, low-priced cars, and set up a large base of service centers to gain market share. Collaboration and partnerships with leading Indian manufacturers can also help to better understand the Indian market. Moreover, ground clearance and suspension should be good enough to drive on India's roads with their elevated speed breakers.

Research Questions

Finally, experts were also asked to suggest several topics for further research and exploration in the Indian context. For example, the *relationship between Indians' purchases of two-wheelers and cars* is worth exploring. Four experts think that if Indians can afford a car they will buy it irrespective of two-wheeler prices, since it is a status symbol. If two-wheelers negatively affect car adoption rates, the Indian government may devise policies to encourage purchase of two-wheelers to slow adoption of four-wheelers. Experts provided mixed comments about such policies, assuming that two-wheeler ownership negatively affects car-ownership in India. Two experts intuitively argued that investment in public transit is the way forward for India, rather than subsidizing two-wheelers; but two others found it an appropriate strategy to contain India's burgeoning car market, with a concern about safety since two-wheelers have much higher fatality rates (Fagnant and Kockelman 2015).

Exploring *the potential for carsharing programs* in India is another meaningful research avenue. Experts agree that carsharing business models should work in large cities with an educated and mobile population (e.g., Bangalore). If carsharing prices are low enough[7] to compete with rental cars and the overall daily cost of car ownership and use, these programs may take off across the nation. However, fleet managers need to incentivize better treatment of shared/rental vehicles or penalize those who abuse the vehicles. Initial target populations may be younger consumers (e.g., 25-35 years old) and households that can just afford a car, but do not yet have one.

It also is worth exploring the *impact of a fuel price hike on vehicle ownership.* Experts feel that Indians' vehicle ownership decisions are not significantly sensitive to fuel prices, yet are sensitive to fuel economy, which suggests inconsistent behavior. Of course, driving miles may fall as fuel prices rise; and some experts believe that lower-income households will then shift from two-wheelers to public transport, while car owners shift to more fuel-efficient two-wheelers. However, two-wheeler sales are not likely to increase since most Indian car owners already own at least one two-wheeler.

More cars on the road raise congestion but improve a state's and nation's productivity. One needs to explore the validity of this argument. If the statement holds true, it raises an important policy question as to whether the government should discourage car purchases in India. Experts think that policy-makers should estimate and compare the changes in equity, GDP, and other performance metrics due to investment in public transit versus the nation's automotive industry. Even if automobile investment is assumed to be more economically productive (and national and state governments encourage it), city governments should take actions to discourage it by investing in transit and non-motorized infrastructure.

Most experts think that a *hike in parking prices* is a key policy for reducing car use in India. This belief needs formal evidence before recommendation, and the experts interviewed were not aware of any published literature in the Indian context.

Lane-use discipline requirements are unlikely to emerge in India anytime soon, due to significant speed differences among bicycles, auto rickshaws, two-wheelers, buses, and cars. However, it would be interesting to see the impacts of lane-use discipline in India. Two experts could suspect that, in such a scenario, two-wheelers will lose their utility to move through the gaps and cars may become equally navigable in India's congested settings, causing more Indians to acquire a car rather than a two-wheeler.

MODELS OF VEHICLE OWNERSHIP USING STATE-BASED CENSUS DATA

Year 2011 demographics for all 35 states of India were obtained from India's Planning Commission (2014), Ministry of Statistics and Programme Implementation (2011), and Census (2011). Two linear regression models were developed with the percentages of households owning at least one two-wheeler and at least one car as the two response variables.

Consider the following model for the two-wheeler (and then four-wheeler) ownership:

$$y_i = \boldsymbol{x_i}'\boldsymbol{\beta} + \varepsilon_i$$

where y_i is the dependent variable (i.e., the share of households owning at least one two-wheeler in Indian state i), $\boldsymbol{x_i}$ is a vector of covariates for state i (including population density and share of households in that state owning at least one personal computer), and $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and ε_i is an independent and identically distributed error term.

Initial model specifications included all explanatory variables, and models were re-estimated using stepwise elimination (by removing the covariate with the lowest statistical significance) until all p-values were less than 0.32, which corresponds to a minimum t-stat of 1.0. A maximum permitted p-value of 0.10 (for statistical significance) was not used here due to the very limited sample size (n=35).[8] If district-level census data had been available (n=640), statistical significance would be greater (and p-values smaller). Thus, any variable whose inclusion makes behavioral sense and has a solid t-statistic remains in the model due to the very limited sample size, which directly impacts statistical significance rather than a variable's practical significance.

The practical significance is generally of more interest to policymakers and planners than statistical significance. This study considers an explanatory variable to be practically significant if its standardized coefficient[9] exceeds 0.5 (so that a 1 standard deviation change in that variable is responsible for at least a 0.5 standard deviation change in the response variable). Table 2 shows the results of regression models, estimated using ordinary least squares (OLS) techniques in SPSS V.16 software.

The positive association of population density with two-wheeler ownership and its negative association with car ownership are intuitive. More populous areas tend to have more frequent transit service, more congestion, and less convenient parking and thus lower car ownership and higher two-wheeler ownership,[10] ceteris paribus in this model. It also appears that states with a higher proportion of occupied housing units tend to have lower car ownership shares. Results suggest that states with a higher fraction of full-time workers tend to have higher car ownership levels, perhaps because full-time employees can better afford cars. The effect of average household size is not accounted for here (due to missing data in public reports), but it and other variables may affect some of these relationships. For example, if smaller households are common in densely developed states, then a lower share of households with cars does not necessarily mean a lower number of cars per capita. The 4+ person household variable used here can pick up some of these effects, but not all.

The results suggest that states with more computer-owning households tend to have higher rates of two-wheeler and car ownership.[11] States with a higher share of large households (4+ members[12]) are estimated to have higher car ownership, ceteris paribus. This result is intuitive because larger households may regularly need a car (rather than a two-wheeler) to accommodate all household members in order to visit their relatives, special events, and other family activities. States with higher shares of households having 2+ more married couples in them (e.g., parents living with their daughter and her husband) are estimated to have higher rates of two-wheeler ownership, everything else held constant. Thus, manufacturers interested in higher sales of four-wheelers may do best targeting their advertising to cities and states with greater shares of higher-income households and/or multi-couple households.

Everything else held constant (in Table 2's OLS model specifications), states with higher shares of rural populations tend to have more car-owning households as a share of all households and fewer two-wheelers. This finding is consistent with those of Dash et al. (2013), and is logical because those residing in rural areas need to travel greater distances for access to education, medical care, markets, legal resources, and so on; and many Indian villages do not have regular bus service for such travel. In terms of investments and policies for improving rural-urban transit-system connections, to reduce the heavy burden of car ownership, India's agencies may want to focus on the less-urbanized states. At the same time, automobile manufacturers and their sales teams may find it most profitable to

set up showrooms and repair service centers in less-urbanized and lower-density locations, thanks to their higher auto ownership rates after controlling for full-time employment levels, computer ownership, and household sizes, as shown in Table 2.

With just six or fewer covariates, each regression model still managed to attain a reasonable fit, with adjusted R-square values of 0.75 for two-wheeler ownership and .89 for car ownership rates, as shown below in Table 2.[13] In terms of practically significant variables, standardized coefficients suggest that the share of households living in rural areas is a key (very practically significant) variable for predicting ownership of two-wheelers and four-wheelers, while computer ownership rates are a very good predictor of car ownership rates, and variables of population density and the share of households with multiple married couples are practically significant in predicting rates of two-wheeler ownership. It is unfortunate that better covariates, like distributions or simply averages of age, income and educational attainment, are not publicly available. It is hopes such data will soon be commonplace in a country as complex and globally important as India.

Table 2: OLS Regression Results for Predicting the % of Households Owning Two-Wheelers and Cars (n_{obs} = 35)

Response Variable % of Households Owning Two-Wheelers	**Coef. Estimate**	**Std. Error**	**Stand. Coef.**	**t-stat.**	**p-value**
Constant	62.61	16.242	--	3.85	0.001
Pop density (persons per square km)	0.003	0.001	**0.501**	3.44	0.002
HHs own computer (% of HH)	0.666	0.292	0.334	2.28	0.030
HHs with 2 or more married couples (% of HH)	1.278	0.292	**0.507**	4.38	0.000
Percent of population in rural areas	-0.562	0.103	**-0.928**	-5.46	0.000
R-Square = 0.784 and Adj. R-square = 0.747					
Response Variable % of Households Owning Cars	**Coef. Estimate**	**Std. Error**	**Stand. Coef.**	**t-stat.**	**p-value**
Constant	-10.69	10.55	--	-1.01	0.320
Pop density (persons per square km)	-0.00052	0.00026	-0.245	-2.28	0.030
Occupied housing units (%)	-0.193	0.102	-0.153	-1.88	0.070
Full-time workers (% of Pop)	0.153	0.072	0.171	2.14	0.041
HHs own computer (% of HH)	0.896	0.082	**1.035**	10.9	0.000
HHs with 4 or more members (% of HH)	0.107	0.070	0.114	1.52	0.138
Percent of population in rural areas	0.147	0.034	**0.560**	4.28	0.000
R-Square = 0.919 and Adj. R-square = 0.899					

Note: Standardized coefficients of practically significant variables are shown in **bold**.

CONCLUSIONS

This paper summarizes existing household- and person-level models of Indians' vehicle ownership decisions, while finding that raw, disaggregate data (or household travel survey data) to develop individual vehicle ownership and use models are almost impossible to obtain without disseminating a new survey. Because more than 75% of all vehicles are two-wheelers and that India offers rather unusual demographics and travel behaviors, one cannot substitute results of data sets and behavioral models developed for other parts of the world. Moreover, most of the disaggregate vehicle ownership models available in the literature (except Dash et al.'s [2013] national examination) are at the level

of single regions. Moreover, existing studies do not offer any disaggregate vehicle ownership models for key Indian metropolitan areas, like Delhi, Bangalore, and Kolkata. In such a diverse country, it is not reasonable to generalize the results of vehicle ownership models developed in other regions of India to these major cities.

Questionnaire-based interviews of travel and vehicle choice experts for India provided multiple valuable insights about factors affecting purchase of cars and two-wheelers, Indians' fuel choices, the electric vehicle and used-vehicle markets, strategies for non-domestic manufacturers in India, and amendments to safety laws. Such conversations also raised a series of relevant research questions affecting current and future vehicle ownership decisions, travel choices, and policies in the Indian context. These research questions include the potential for carsharing programs in India, lane use discipline requirements, the car-ownership impacts of changes in fuel and parking prices, and the relationship between two-wheeler and car ownership rates. In essence, the Indian automotive market provides complex and unexplored policy-related research avenues that will require thoughtful investigation.

In the absence of disaggregate household travel survey data for India, this study developed two OLS regression models to estimate household ownership rates of two-wheelers and cars. It is worth noting that the share of households residing in rural areas and computer ownership rates (if income and education variables are not available) have practically significant effects on car-ownership shares. However, due to the issues with data aggregation, and thus the potential for "ecological fallacies," one cannot generalize too much from state-level regression results for individual-level vehicle ownership choices (Schwartz 1994). A need for new disaggregate level vehicle ownership models in key regions of India, which still do not have such models, is clear.

Endnotes

1. Although India and China have low motorization indices, the total number of vehicles present in both countries is remarkable.

2. Kumar and Krishna Rao (2006) contacted 2,063 respondents (using skilled interviewers in face-to-face settings), and only 357 valid and completed surveys were obtained.

3. These estimates are based on a projected per-capita income growth of 6.5% per year from 2005 to 2030, and 5.2% per year from 2030 to 2050.

4. In a trip production model, vehicle ownership is an important explanatory variable, but the reverse causality or endogeneity (the effects of trip frequency on vehicle ownership decisions) is generally neglected in conventional models, which assume that the longer-term vehicle ownership decision is an exogenous input to trip generation, but that may not be the case.

5. In developing countries, people are averse to disclosing their income information and may understate it due to tax-related concerns. Moreover, seasonal fluctuation in the incomes of agriculture-based households is relatively high, as compared with variations in their expenditures.

6. The expert questionnaire had 19 questions with multiple parts. The experts were selected from the UT Austin alumni network and acquaintances of the author with researchers working on similar topics. On average, the questionnaire took 30 to 45 minutes to complete. There was no incentive provided, which is why the response rate is relatively low at approximately 25%.

7. It is worth noting that insurance is less expensive and maintenance/repair labor costs are lower in India than in developed countries.

8. Obtaining data is a difficult task in developing countries such as India. Here, the candidate variables are those found in the regression models for ownership of two-wheelers and ownership of cars, plus the literacy rate, which did not deliver a t-statistic > 1 or < -1 in either of the models. Candidate variables were not selected using any specific criteria. Instead, as many variables as possible were obtained using publicly available data sets across Indian states.

9. A standardized coefficient is the number of standard deviations change in a dependent variable per one standard deviation increase in the explanatory variable. Explanatory variables with higher standardized coefficients are more practically significant.

10. Two-wheelers need less space than cars and so are easier to drive and park in congested settings.

11. One cannot obtain variables such as average income, education levels, etc. from open-access data, so they were not included in this research. However, shares of households owning computers can be viewed as a partial proxy for income and education.

12. A household size of four persons was chosen as the threshold here, because three people can (and often do) travel together on two-wheelers in India.

13. Higher R^2 values are a common outcome of predictive models using aggregate (e.g., state-level) data. These fit statistics are expected in these state-level analyses. More information can be found here: http://statisticshowto.com/aggregation-bias/.

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Pass the Salt: Markets for Grain Shipping on the Great Lakes

by Logan Pizzey and James Nolan

We assess the structure of grain shipping within the Great Lakes and St. Lawrence Seaway system. While U.S. grain exports ship from the port of Duluth, Minnesota, Canadian grain exports ship from several ports located on the Lower St. Lawrence Seaway. While North American grain exports moving from west to east can be transported in several different ways, due to data limitations our focus in this analysis is on the so-called saltie shipping market. While our findings are somewhat unexpected, they give us some unique insight into the nature of this crucial yet understudied transportation market.

INTRODUCTION

The Great Lakes and St. Lawrence Seaway (GLSLS) is a major inland waterway system stretching over 3700 kilometers into the North American continent. As a historically important transportation corridor connecting the inland cities and industries of North America to the Atlantic Ocean, the system has transported over 2.3 billion tonnes of cargo in the last 50 years, worth over US$350 billion (Jenish 2009). Major commodities transported on the corridor include grain, coal and coke, iron ore, limestone, petroleum products, cement, and aggregates. Overall, the GLSLS has a wide-reaching impact on a variety of industries and still plays a vital role in the North American economy.

Very little is currently known about the market structure of the waterborne shipping sector that serves the Great Lakes. Industry level data indicate that while some shipping markets on the lakes look to be competitive, others seem less so. Insights on market structure should prove useful to North American policymakers and to those users (commodity shippers) who rely on the Great Lakes for goods movement. While many commodities move through the Great Lakes, for clarity we focus this analysis on a single commodity (grain) that is shipped from both the U.S. and Canada over the Great Lakes. Using a historical sample of waybill data on grain movements over the Great Lakes, we evaluate the degree of market competition that existed at that time in Great Lakes grain shipping. While our findings are interesting from a transportation economics perspective, in many ways they raise more questions than they answer.

CHARACTERISTICS OF GREAT LAKES ST. LAWRENCE SEAWAY SHIPPING

There are three major types of cargo ships that operate on the GLSLS. The first of these are the U.S. flag lakers. These ships concentrate on intra- and inter-lake trading because their large size restricts them to the two upper Great Lakes (USDOT 2013). The second type of ships used are Canadian lakers. These are typically built to a standard maximum of 740-feet long in order to fit through the locks of the St. Lawrence Seaway (Jenish 2009). These vessels conduct the majority of their business transporting cargo between various ports on the Great Lakes, as well as deep water transfer ports located on the Lower St. Lawrence. The latter ports are the points where seaway cargo can be transferred between lakers to relatively larger ocean-going vessels exiting the seaway to the Atlantic Ocean. The other type of ship used on the Great Lakes system are known as salties. While these ships are built to pass through the locks of the GLSLS, unlike lakers, salties are also capable of operating on the open ocean. Thus, instead of only operating on routes between Great Lake ports and the Lower St. Lawrence transfer terminals, salties can move cargo directly from Great Lake port origins to international destinations.

GRAIN TRANSPORTATION ON THE GREAT LAKES

When Canadian Prairie grain shippers want to move grain from inland terminals to international consumers, they have three major choices for shipping grain through Eastern Canada. The first option available is to move their grain east from inland terminals to lakehead terminals by rail, load the grain onto a laker at the port of Thunder Bay, move the grain east through the Great Lakes system, and finally trans-load the grain onto oceangoing vessels at Lower St. Lawrence export terminals. The second option is for grain shippers to move the grain to lakehead by rail but load the grain at Thunder Bay onto a saltie, which can transport grain directly to international customers. Finally, grain shippers also have the option of transporting grain across Canada to the various Quebec export terminals by rail, where it would then be loaded onto oceangoing vessels. Note that the latter choice bypasses the Great Lakes system completely.

While the majority of grain moving to eastern ports is moved by laker, the proportion of grain moved by salties has increased significantly in recent years (Heney 2016). It should also be noted that there is some interdependence between the movement of grain in the Great Lakes by saltie and the other transportation modes. Due to vessel draft limitations in the GLSLS, salties are often not able to load to full capacity when they take on a load of grain at ports such as Thunder Bay in Canada or Duluth in the U.S. However, once vessels have traversed the GLSLS, they will often stop at grain transfer facilities on the lower St. Lawrence in order to fill their holds to capacity before departing for their international destinations (Heney 2016). In effect, salties are somewhat dependent on either rail or Laker movement of grain to the St. Lawrence transfer terminals, especially if owners want to ensure they are filled to capacity before crossing the ocean.

SALTIES AND LAKERS

Given the multi-faceted nature of Great Lakes grain movement, we need to highlight that the data used for this research consist only of waybills for oceangoing salties that transported grain over the GLSLS. While both salties and lakers might appear as being outwardly similar in their provision of grain transportation on the GLSLS, as we have outlined there are some interesting distinctions between the two. And while lakers have been the dominant mode for the movement of grain out of the important port of Thunder Bay, more recent information seems to suggest that grain shippers are increasingly turning to salties (Thunder Bay Port Authority 2015). Next, we will highlight some of the differences between the two types of Great Lakes shipping, and explore potential explanations for the recent increase in the use of salties for transporting grain out of the Great Lakes.

While salties possess the same size restrictions as lakers due to the GLSLS lock system, by design they permit delivery of Great Lakes originating cargo directly from inland ports to overseas destinations. Grain delivery directly to the end customer eliminates the cost of trans-loading grain at one of the (six) major grain terminals along the lower St. Lawrence. By extension, one disadvantage to using the so-called "Seawaymax" salties for trans-oceanic transportation is that their maximum capacity is significantly less than the largest oceangoing ships that are commonly used to transport grain from other North American deep water ports. While the largest of the Seawaymax bulk carriers have cargo capacities of around 38,000 tonnes, commonly used Panamax ships have capacities of up to 80,000 tonnes (Maritime Connector 2016). Indeed, Canadian grain export facilities at Port Cartier (on the St. Lawrence) have the ability to load even larger vessels, including those with capacities of up to 100,000 tonnes (SLSMC 2002).

Another important difference between the two ships and the markets they serve is that because salties can move cargo to international destinations, no cabotage (e.g., interport movement limits on foreign flagged vessels) laws apply to them. This effectively removes one of the major anti-competitive forces that still restricts the domestic laker market. For example, consider a saltie carrying Canadian cargo. Since saltie cargo is not typically moved between two Canadian ports,

this effectively allows cargo to be transported by vessels operating under any international flag. While there exists a qualified set of companies that provide the majority of saltie service on the Great Lakes system (LeLievre 2014), in effect, the Great Lakes saltie trade is open to entry by any international shipping firm, provided their vessels can fit through the Seaway. We note that even with such market openness, currently there is still a strong Canadian presence in the bulk vessel industry operating on the Great Lakes. Two Canadian companies headquartered in Montreal remain important players in the aaltie market. They are Fednav Limited, operating a fleet of 38 bulk carriers, and Canadian Forest Navigation, which operates 27 bulk carriers (LeLievre 2014).

While Lakers are confined to operating in the GLSLS so that their operating numbers are relatively consistent, the number of salties operating in the system can fluctuate widely depending on market conditions. In effect, the overall strength of the American economy and the derived demand for major industrial inputs remains one of the single most important factors affecting the saltie market operating in the GLSLS (Heney 2016). To this end, semi-finished steel is the input that often dominates inbound trade over the GLSLS (SLSMC 2002). Globally, international steel producers, such as Brazil, the European Union, China, South Korea, Turkey, and others, ship semi-finished steel in the form of steel slabs, billets, coils, and rods to North American industry located on the Great Lakes using oceangoing (i.e., saltie) vessels (International Trade Administration 2016). Once an inbound cargo like steel has been delivered, these ships are then able to pick up other commodities, such as grain, from port terminals around the Great Lakes for delivery back to international markets. Even today, we note that for many of these shipping companies, transporting steel to North America is their primary business, while in many cases any grain that they might transport is loaded as a backhaul (Heney 2016).

Table 1: Recent Schedule of Thunder Bay Laker and Saltie Calls

Year	Laker Calls	Saltie Calls	% Moved by Saltie	Tonnes Moved
2010	252	62	19.7%	5,239,594
2011	337	51	13.1%	6,267,457
2012	335	72	17.6%	6,456,533
2013	176	53	23.1%	5,403,460
2014	308	127	29.1%	8,325,099
2015	288	125	30.2%	8,018,638

Adapted from Thunder Bay Port Authority, 2016

Looking at Table 1, we note a surge in salties using the port of Thunder Bay. Part of this surge can likely be attributed to recent strength in American steel import demand. American steel imports rose from a post-recession low of less than one million tonnes (imported in June 2009) to a recent high of four million tonnes in October 2014 (International Trade Administration 2016). But relevant to our analysis, at least some of the increase in grain traffic through Thunder Bay, and concurrently some of the increase in these saltie calls could be attributed to the record Canadian crop that occurred in 2013. So while steel surely dominates, we postulate that grain still has some influence on the saltie market operating on the Great Lakes.

ANALYTIC FRAMEWORK

The basis for our market analysis is a comparison of historical rates between Saltie grain traffic originating out of the Great Lakes and oceangoing grain traffic originating out of ports along the

Lower St. Lawrence. The method of analysis that will be used to examine the rates consists of econometric tests for rate cointegration.

Prior related literature motivates several examples of this kind of testing to assess market competitiveness. To start, Hänninen (1998) used cointegration tests to assess whether the law of one price held in the soft sawnwood import market in the United Kingdom for lumber originating from four different countries. Similarly, Abdulai (2000) tested for cointegration by examining the price linkages between three major Ghanian maize markets. Siliverstovs et al. (2005) compared regional natural gas prices to both the world price of oil as well as natural gas prices in other regions, again statistically testing integration between the markets. All of these authors suggest that if there is evidence of statistical integration among markets, arbitrage must be occurring and competition is active across the individual markets.

Finally, in assessing the validity of law of one price in agricultural product markets, Sexton et al. (1991) suggested that information regarding the level of actual integration between two markets can provide evidence regarding the competitiveness of the markets. When two markets are evaluated to not be cointegrated in a statistical sense, these authors suggest other possible causes for this situation. Two of their suppositions to be explored in this paper include the possibility that the two markets are not linked by arbitrage, or alternatively, that there may be impediments to efficient arbitrage.

In this research, we hypothesize that if the saltie market in the GLSLS is competitive, the data should indicate that rates originating in the Great Lakes are cointegrated with rates for grain originating in the Lower St. Lawrence. If we cannot find evidence of integration between the two markets, it suggests there are market forces hindering arbitrage between the two markets or otherwise limiting the level of competitiveness in the Great Lakes saltie market. In order to investigate whether or not the sets of rates are cointegrated, we conduct a basic Engle-Granger test for cointegration on the Seaway rate data.

Briefly, the Engle-Granger cointegration method is a well-established econometric test used to determine whether or not two integrated of order 1 (I(1)) time series processes are cointegrated. Formally, if $\{y_t : t = 0,1, \ldots\}$ and $\{x_t : t = 0,1, \ldots\}$ are both non-stationary I(1) processes, then x and y will be cointegrated if for $\beta \neq 0$, $y_t - \beta x_t$ is in fact an integrated of order zero (I(0)) stationary process (Wooldridge 2013). In other words, if x and y are cointegrated, there will be a tendency for the "spread" between them to return to its mean value over time. However, if x and y are not cointegrated, there will be a tendency for the "spread" between them to widen over time. It is the structure of these spatially separated transportation rates measured over time that we wish to evaluate in this research.

DATA AND EMPIRICAL METHODS

The dataset used in this analysis is a collection of waybills obtained from oceangoing salties transporting grain from Great Lakes and Lower St. Lawrence ports to a variety of international destinations. While attempts were made to obtain more recent GLSLS data, the data we managed to obtain span from 1996 to 2001, and include information such as the port of origination, destination, cargo type, date that the shipment began and the rate ($U.S.) charged per tonne. For shipments originating in the Great Lakes over this time frame, 30 observations are specifically listed as originating from the Port of Thunder Bay, 76 from the Port of Duluth, and 67 other shipments with various other origins. Included in this latter category are shipments listed ambiguously as originating from the "Great Lakes" as well as the "Lakehead" (in reference to a shipment either from Thunder Bay or Duluth). Meanwhile, 196 shipments over this interval in our data are listed as originating from ports along the Lower St. Lawrence.

Since movements (observations) in our data did not occur at regular intervals, we tried to match observations originating from the Great Lakes with observations from the Lower St. Lawrence. Due

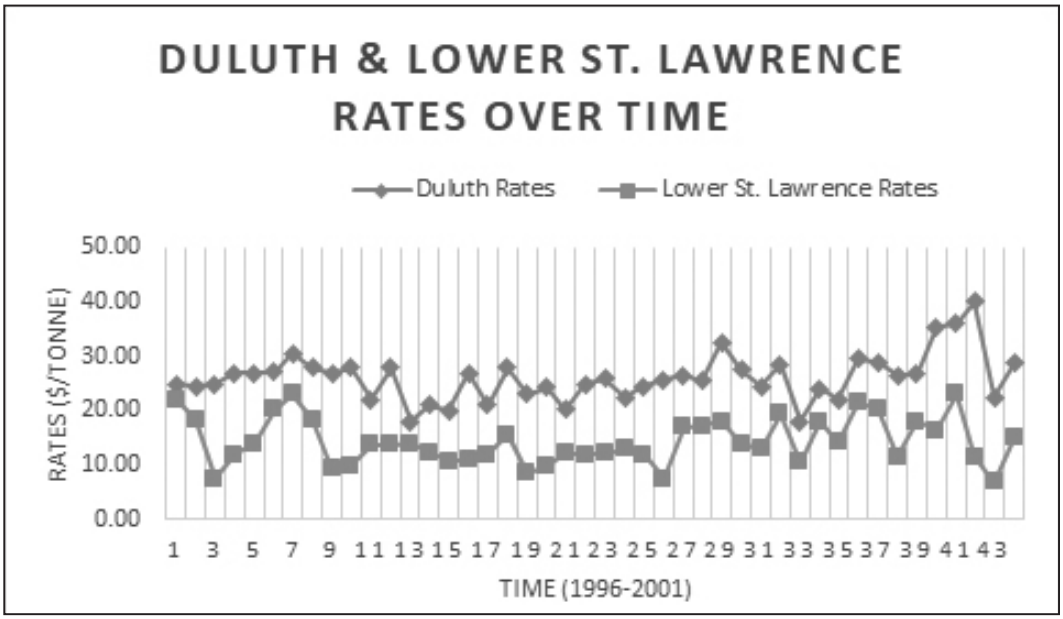
to the relatively small sample size overall, a decision was made for statistical purposes to match freight rate market observations as long as the movements occurred within two weeks of each other. We also attempted to pair shipments between Thunder Bay and Duluth, Thunder Bay and the Lower St. Lawrence, and Duluth and the Lower St. Lawrence. However, we found that the Thunder Bay-Duluth and Thunder Bay-St. Lawrence combinations produced too few rate data pairings to provide meaningful statistical results. Thus, the remaining 44 Duluth-St. Lawrence pairings will be analyzed further.

Descriptive statistics of this latter dataset are provided in Table 2. Figure 1 illustrates various fluctuations in the two sets of grain rates over the time period studied.

Table 2: Descriptive Statistics of Duluth & St. Lawrence Rates

	Duluth	St. Lawrence
Mean Rate ($/tonne)	26.11	14.36
Standard Deviation	4.414	4.298
N	44	44

Figure 1: Duluth & Lower St. Lawrence Rate Movements



Source: Authors

After pairing Duluth and St. Lawrence movements by date, each set of rates was tested in order to ensure that each followed a non-stationary I(1) process. By definition, before a test for cointegration can be performed, it is necessary to ensure that the variables being tested are I(1) processes (Wooldridge 2013). To do this, an Augmented Dickey-Fuller (ADF) test was performed on each of the subsets of rates. However, before an ADF test could be performed, it was necessary to determine the optimal lag order to use in the test.

Ivanov and Kilian (2005) suggest that in small sample sizes with 120 observations or less, the Schwarz Information Criterion (SIC) is the most accurate way of estimating the correct lag order. Due to the limited number of observations, the SIC was used to estimate the optimal lag order to be

used in each of the ADF tests that were performed throughout this study. The optimal SIC lag order was identified using the Stata13© software.

After verifying that both sets of rates were non-stationary I(1) processes, the next step in the Engle-Granger cointegration test process is to run a basic regression on the two rates. Subsequently, the residual from this regression is tested using another ADF test to determine whether or not the resulting residual is the necessary I(0) stationary process or not. In effect, if the residual of the regression is found to be an I(0) process, the variables are considered to be statistically cointegrated. In this analysis, the following general form of the regression of the Duluth rates on St. Lawrence rates was performed:

$$y_t = \hat{\beta}_0 + \hat{\beta}_1 x_t + \hat{u}_t$$

Where: y_t = Prices of Duluth rates in \$/tonne

$\hat{\beta}_0$ = Estimated intercept from the regression

$\hat{\beta}_1$ = Estimated slope coefficient of $_t$

x_t = Prices of St. Lawrence rates in \$/tonne

$\hat{u}_t$ = Estimated residuals from the regression

Following the regression estimation, the SIC criterion was applied to the estimated residuals in order to determine the optimal lag order to use in the ensuing ADF test. Subsequently, an ADF test was performed on the residuals from the regression. This is done in order to determine if the null hypothesis that the residuals follow an I(1) process could be rejected, indicating the two sets of rates are cointegrated.

RESULTS

After plotting the rates for cargo originating out of Duluth, it appeared there was a basic upward trend in the data over time. This was important to identify. When conducting testing to confirm the presence of a unit root in this data, in fact we had to perform a variation of the ADF test that accounts for an upward trend (see Hamilton 1994). Before performing this modified ADF test, we had to specify the optimal lag order to use. The optimal SIC generated lag order for the Duluth rates was found to be unity.

The Lower St. Lawrence rates were also plotted over time, but it was far less obvious whether or not there was any kind of significant directional trend over time. In order to be certain, an ADF was performed assuming an upward trend over time, and, no trend over time. As with the previous set of rates, optimum lag orders were selected using the SIC criterion. In the case of St. Lawrence rates, the optimum lag length was found to be six lags.

After performing an ADF test on the Duluth freight rate set, we were unable to reject (at all confidence levels) the null hypothesis of Duluth rates following a non-stationary I(1) process. Two different ADF tests were performed on the St. Lawrence freight rate set and the null hypothesis of integration of order one could not be rejected at all confidence levels across both of the tests. After assessing that both of the variables followed I(1) non-stationary processes, the next step in checking for cointegration consisted of running a simple regression of Duluth rates on St. Lawrence rates.

Plotting the residuals of this regression, there also appeared to be an upward trend in the data. This situation was once again corrected for when performing our ADF test. The SIC was used again and an optimal lag order of unity was found. Next, another ADF test was performed, the results of which are displayed in Table 3. As the test shows, the null hypothesis that the regression residuals follow an I(1) process cannot be rejected at any reasonable confidence interval. Thus, somewhat contrary to our prior test, we conclude that Duluth freight rates and St. Lawrence freight rates within this time interval are not statistically cointegrated.

Table 3: Augmented Dickey-Fuller Test For Unit Root (Residual)

Interpolated Dickey-Fuller						
	Test Statistic	1% Critical Value	5% Critical Value		10% Critical Value	
Z(t)	-3.024	-4.224	-3.532		-3.199	
MacKinnon approximate p-value for Z(t) = 0.1256						
D. residual	Coef.	Std. Error	t	P>|t|	95% Conf. Interval	
residual						
L1	-0.6011431	0.1988203	-3.02	0.004	-1.003634	-0.198653
LD	-0.2677789	0.1563263	-1.71	0.095	-0.5842449	0.0486872
_trend	0.041974	0.0525362	0.80	0.429	-0.06438	0.148328
_cons	-0.7582427	1.324328	-0.57	0.57	-3.439204	1.922718

Source: Author

DISCUSSION

Considering that saltie rates for grain originating in Duluth in this period were not cointegrated with oceangoing rates for grain originating out of ports in the Lower St. Lawrence, we need to reassess what occurred within these seemingly linked freight transportation markets. We start this process by considering the implications work by Sexton et al. (1991) describing possible reasons why two apparently linked markets may not in fact be price or rate cointegrated.

While Sexton et al. (1991) list the absence of rate or price arbitrage mechanisms between two markets of interest as one possible reason for a lack of rate cointegration, we believe that this explanation is unlikely with respect to the Great Lakes saltie market. While there are certain physical and regulatory restrictions that impose limitations on the efforts of foreign shippers to enter the Great Lakes grain transportation market, the market is certainly not closed to outside competitors. As mentioned earlier, while there are few domestic saltie operators, LeLievre (2014) notes there are a number of international bulk carrier vessels that have always operated on the Great Lakes. In turn, this presence presumably helps keep the entire Great Lakes freight market (across a number of commodities, including grain) at a reasonable level of competition.

Given this, there seems to be a much stronger case for arguing that there may be an inefficiency in arbitrage that exists regarding limitations imposed on international ship capacity entering the Great Lakes market, as compared with the Lower St. Lawrence market. Although the magnitude of these effects is not well-documented, there are a number of issues that, at least from a theoretical perspective, might limit the ability of international saltie shippers to effectively compete in the Great Lakes market.

For example, one of the major physical limitations that reduces the level of competitiveness in the Great Lakes grain shipping market is the constraint imposed on vessel size by both the locks of the Welland Canal and the St. Lawrence Seaway. When the seaway was first opened, it was large enough that about 90% of the world's freighters at the time could pass through its locks. However, this percentage has fallen to less than 35%, mostly due to economies of scale and advancements in ship-building (Maritime Connector 2016). As the size of oceangoing bulk carriers has continued to increase, shipping companies operating on the Great Lakes have been constrained by the size limitations imposed by the GLSLS. While most Canadian ships operating on the GLSLS have been built to Seawaymax standards (740-feet long by 78-feet wide), overall bulk carriers on the lakes are constrained to a maximum load capacity of approximately 38,000 metric tonnes (LeLievre 2014).

By comparison, the common Panamax class of ocean bulk carriers have capacities ranging from 60,000 to 80,000 tonnes, with lengths often over 1,000 feet (Maritime Connector 2016).

Another challenge for the saltie shipping industry is the additional costs incurred when shipping through the GLSLS. Any international-flagged vessels using the seaway are subject to pilotage rules that result in additional costs because of the need to hire the services of a specialized pilot for passage through specific parts of the waterway system (Stewart 2006). Records from a Canadian Parliamentary subcommittee meeting in 2003 estimate that the average saltie would incur about US$200,000 of expenses in the form or seaway tolls, marine service fees, port dues, pilotage services, stevedoring fees, tuck service fees, and port warden fees for every roundtrip through the GLSLS (Parliament of Canada 2003).

Mindful of these potential reasons that could help explain our findings, there is likely another key factor contributing to our finding of a lack of rate integration between these two shipping markets. We offer that the back-haul pricing issue identified in the freight transportation literature offers another potential explanation as to why these two seemingly linked transportation markets were not found to be statistically cointegrated.

Boyer (1997) highlights that although commodities will be moved from one point to another, the vehicles that transport them must typically also go on a round trip back to their origin. In a round-trip freight movement scenario, a vehicle will operate on its primary front-haul route, and demand for this transportation service is necessarily greater than any transport demand that might exist (if at all) on the associated back-haul route. This situation is known more colloquially as the back haul problem. Subsequently, if costs are to be allocated efficiently, a front-haul will typically be operated using a higher freight rate (i.e. its share of the cost of the full roundtrip) than the back-haul.

This situation for ocean shipping was studied by Fan et al. (2014). They found that on ocean shipping routes with large trade imbalances that generate significant differences in the demand for transportation services between the back-haul and front-haul routes, freight rates over the two routes often fail tests for rate cointegration. This observation raises the possibility that the lack of cointegration found between the Duluth and Lower St. Lawrence rates may be due to the presence of a back-haul issue. As alluded to earlier, during the time of our analysis, this effect could have been generated by the inbound movement of foreign steel to U.S. Great Lakes ports by saltie operators, who subsequently used grain as a back-haul when grain to move out of the Great Lakes was available. More research and better data will be needed to further explore the importance of the back-haul issue on freight rates (and how this affects the transportation market structure) applied to other important commodities moving within the Great Lakes system.

Finally, as a caveat to this discussion, we need to reiterate that the available data were not a true co-temporal time series of the type typically used to measure cointegration. Instead, we formulated an approximation as necessitated by temporal limitations on the freight movements found in the data. Since freight movements (data points) from the two studied markets were only approximately matched across time, there exists the possibility that our analysis could be adversely affected if shipping rates happened to fluctuate significantly within the chosen two-week time period for rate matching. However, discussions with the data provider (Maritime Research Inc.) indicated that within a typical two-week time frame over the chosen sample period, shipping rates on the Great Lakes remained fairly stable. We conclude that the manner in which we constructed our matching freight rate series to test for cointegration across these two markets did not do serious injustice to the data nor bias our findings.

CONCLUSIONS

With the relative lack of prior industrial analysis of this key transportation sector, the initial goal of this research was to assess market structure for grain transportation on the GLSLS. Due to a number of data limitations, we limited the latter analysis to a study of the diverse saltie shipping industry operating throughout the Great Lakes. By utilizing a detailed dataset of waybill information on international grain shipments with origins in both the Great Lakes and the Lower St. Lawrence Seaway, we ultimately developed statistical tests of rate cointegration across U.S. and Canadian grain transportation markets on the Great Lakes.

Our initial supposition was that if Canadian and U.S. grain transportation movements on salties within the GLSLS was found to be statistically rate cointegrated, then during the time of our sample this market was competitive, to the overall benefit of grain shippers in the region. However, we were unable to conclude that grain shipping rates within these two seemingly linked transportation markets were statistically cointegrated.

This surprising finding led us to posit alternative explanations about what must have been occurring in the saltie market (relevant to grain transportation) at that time. One possibility we discussed is that there are certain physical and regulatory restrictions that limit the ability of international saltie operators to compete with domestic operators, thus reducing the competitive efficiency of the market. But another possible explanation of our findings stems from a back-haul issue with respect to grain movement on the lakes, a situation that might have affected saltie grain rates out of Duluth in particular. If high U.S. demand for foreign steel was effectively driving the saltie market in the GLSLS, back-haul grain movements out of Duluth may have been priced at somewhat discounted rates as compared with their Canadian originated counterparts. The import patterns of foreign steel into Canada very likely occurred at different times and places than in the U.S., leading to the possible breakage of any potential linkages for grain movement on salties across the two markets at that time.

For this analysis, much of the available data were collected before a number of major changes occurred in the Canadian grain handling and shipping industries. For one, the removal of the import duty on ships from foreign shipyards was lifted by the Canadian government in 2010, an event that was followed by a significant number of vessel purchases by several players in the Great Lakes grain handling industry. Additionally, the removal of the former Canadian Wheat Board's single-desk marketing power in 2012 drastically altered the nature of Canadian grain shipping through the Great Lakes. Therefore, while this study provides some unique insight into the historical nature of grain shipping on the Great Lakes, it remains unclear how these latter developments have altered the Great Lakes grain shipping market.

Considering the lack of available data and the growing importance of this transportation sector, we offer that more research is needed to gain insight not only into the structure of the modern saltie market, but also into the large and poorly understood laker shipping market. Anecdotally, the latter would appear to possess several problems related to market structure that may be affecting commodity shipments. As of this writing, we note that the laker market is effectively dominated by just two major companies.

Linked to this research, it would be insightful to investigate the degree of market integration that might exist between lakers and oceangoing bulk carriers. Due to the lack of general knowledge about market structure in the Great Lakes bulk transportation market, it is our opinion that any further research into Great Lakes shipping will prove to be of high value, due in part to the potential for future market growth that exists over the GLSLS. In particular, many agree that the capacity of the waterway is underutilized, especially with respect to grain transportation. Additional research should help identify some of the reasons for this situation and suggest ways to improve utilization of this vast and critical inland waterway.

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An Application of Decision Tree Models to Examine Motor Vehicle Crash Severity Outcomes

by Jill M. Bernard Bracy

Classification and Regression Tree (CART) and chi-square automatic interaction detection (CHAID) decision tree models are estimated and compared to examine the effect of driver characteristics and behaviors, temporal factors, weather conditions, and road characteristics on motor vehicle crash severity levels using Missouri crash data from 2002 to 2012. The CHAID model is found to significantly better discriminate among severity outcomes, and results suggest that the presence of alcohol, speeding, and failing to yield lead to many fatalities each year and likely have interactive effects. Decision rules are used to identify changes in driving policies expected to reduce severity outcomes.

INTRODUCTION

Motor vehicle crashes are a leading cause of death in the United States (Centers for Disease Control and Prevention 2015), cost Americans approximately $277 billion annually in lost wages, rehabilitation, and medical care (Blincoe et al. 2010), and render serious psychological burdens such as grief, stress, depression, guilt, and travel anxiety for victims and their families (Mayou et al. 1993). Because of these devastating effects, many researchers have attempted to better understand the factors that affect motor vehicle crash severity, yet relatively little research has employed decision trees as the methodological approach used to gain greater insight into relationships among variables in the crash data.

Accordingly, decision tree models are estimated to gain greater insight into interactive effects in motor vehicle crash data and to examine how crash severity differs with numerous possible explanatory variables. Classification and Regression Tree (CART) and chi-square automatic interaction detection (CHAID) decision tree models are estimated using Missouri crash data from 2002 to 2012, and factors examined include driver characteristics and behaviors, temporal factors, weather conditions, road characteristics, and crash severity levels. The explanatory power of the CART and CHAID models are compared using the area under the receiver operating characteristic (ROC) curve on a hold-out sample. To provide a context for understanding the relative reduction in overall risks, outcomes are examined to determine annual upper and lower bounds on the changes in the number of drivers involved in fatal, injury, or property damage only crashes if selected contributory circumstances are eliminated. Decision rules are then used to identify changes in driving policies likely to reduce severity outcomes.

LITERATURE REVIEW

Relatively little research has employed such an approach, yet Savolainen et al. (2011) remarked that decision tree models are an effective data mining technique. Abdel-Aty and Keller (2005) claimed that tree-based regression improves the understanding of the importance of specific factors on individual levels of severity. Oh (2006) concluded that variables associated with injury severity levels may not be the cause of severity, and additional research in this area is necessary. Abay (2013) called for a more encompassing and alternative model specification for injury severity data analysis.

Sohn and Shin (2001) developed decision tree, neural network and logistic regression models to assess the factors that affect traffic crash severity in Korea. The classification tree identified the six factors used in the neural network and logistic regression models (accident mode, road width, car shape, speed before accident, violent driving, and protective device). Model results revealed protective device (i.e., safety belt use or helmet improperly worn) as the most influential variable for classification of crash severity.

Bayam et al. (2005) examined existing literature that used CART models to predict the occurrence of a crash or non-crash, given driver, roadway, vehicle, and other variables. The authors suggested the small sample size to be the cause of the poor predictive power in the test data; and, as a result, findings were not robust enough to be generalizable. However, the authors claimed that a larger data set "could be quite useful for this type of application" (p. 623), and concluded that data mining should be used to discover unknown relationships for crashes for senior and teenage drivers.

Abdel-Aty and Keller (2005) hypothesized that crash injury levels were impacted by crash and intersection specific characteristics. Expanding upon Abel-Aty (2003), the authors developed ordered probit models to assess 33,592 crashes that occurred in 832 intersections in Florida in 2000 and 2001. The study presented a hierarchical tree-based regression model to estimate the expected crash frequency for each crash severity level. Results indicated that the most significant factors for no-injury crashes, possible injury, non-incapacitating injury and incapacitating injury are traffic volume of the major road, the number of lanes on the minor road, the number of exclusive right-turn lanes, and the average daily traffic on the minor road, respectively. The authors concluded that the models should be developed for each level of severity as opposed to predicting the overall severity level, and the tree-based regression improves the understanding of the importance of specific factors on individual levels of severity.

Yan and Radwan (2006) used the classification tree approach to investigate factors of rear-end crashes that occur at signalized intersections. The 2001 Florida crash data used were restricted to two-vehicle, rear-end collisions, and the striking driver was the at-fault party. Model results suggested that drivers under the age of 21 and over 75 have the greatest risk of rear-end collisions. As a result, the authors recommended speed limit reduction to 40 mph at signalized intersections, enforcement for reducing alcohol intoxicated drivers, and additional education for drivers under the age of 21 for reducing rear-end crashes at signalized intersections, and concluded that the classification trees are an appropriate approach in investigating crash propensity.

Chang and Wang (2006) developed a CART model to examine the impact of gender, age, sobriety condition, crash location, vehicle type, contributing circumstance, and collision type on crash severity using 26,831 observations from crashes occurring in 2001 in Taipei, Taiwan. Model results illustrated an initial split based on vehicle type, and suggested that bicyclists, motorcyclists, and pedestrians have the highest risk, and contributing circumstance, collision type, and driver action are important in determining crash severity. The authors concluded by calling for future work in comparing CART model results with traditional models such as ordered probit and logistic regression models.

Abellán et al. (2013) developed decision trees to analyze traffic crash severity for motorcyclists in Granada, Spain. The authors extracted single-vehicle crash observations that occurred on two-lane rural highways from 2003 to 2009 for a total of 1,801 observations, and identified the following rules as having a high risk of a severe injury outcome for motorcyclists: when only one occupant was involved in a single vehicle crash, when at-fault motorcyclists were involved in a run-off-road crash in favorable weather conditions, when male motorcyclists were involved in a run-off-road crash as the result of driver characteristics, and when male motorcyclists were involved in a run-off-road crash in favorable weather. Findings inferred these additional rules to be a high risk of killed/seriously injured crashes on two-lane rural highways when no safety barriers are in place: motorcyclists with no-restrained site distance, crashes in the evening in good weather conditions with no lighting, and crashes with pedestrians during favorable weather when the driver is male.

The authors concluded that the method allowed for a high number of rules to be identified, and the method could be extrapolated for studies on other datasets.

Eustace et al. (2014) employed decision tree models in conjunction with generalized ordered logit models to examine factors that contribute to injury severity for run-off-road crashes in Ohio. Important interactions identified by the decision tree model included: females on higher posted speed limits have higher risk of injury; males with drug involvement and a higher posted speed limit have a higher risk of injury; alcohol use on a road with speed limits over 40 mph have higher risk of injury; and male drivers in crashes on wet road surfaces have higher risk of injury. The authors concluded that not only does the decision tree model analysis identify significant factors of injury severity, it also allows for the detection of multi-level interactions.

Recently, Kahn et al. (2015) used decision trees in conjunction with ordinal discrete choice models to analyze crash severity of cross-median crashes occurring in Wisconsin from 2001 to 2007. The authors claimed that the tree models revealed further information about the crash severity outcome and offered advantages regarding variable redundancy issues.

Drawing upon prior crash severity literature (presented in Table 1), variables suggested to affect crash severity include age, gender, number of occupants, speed limit, light conditions, weather conditions, road conditions and characteristics, and contributing circumstances.

Table 1: Variables Suggested by Reviewed Literature to Affect Crash Severity

Variables	Reviewed Literature
Age	Kuhnert et al. (2000); Abdelwahab and Abdel-Aty (2001); Abdelwahab and Abdel-Aty (2002); Bédard et al. (2002); Khattak et al. (2002); Abdel-Aty (2003); Khattak and Rocha (2003); Delen et al. (2006); Lu et al. (2006); Schneider et al. (2009); Haleem and Abdel-Aty (2010); Rifatt et al. (2011); Yasmin and Eluru (2013)
Gender	Kuhnert et al. (2000); Abdelwahab and Abdel-Aty (2001); Abdel-Aty and Abdelwahab (2004a); Abdel-Aty and Abdelwahab (2004b); Ulfarsson and Mannering (2004); Delen et al. (2006); Islam and Mannering (2006); Savolainen and Ghosh (2008); Schneider et al. (2009); Malyshkina and Mannering (2010); Schneider and Salovainen (2011); Eustace et al. (2014)
Number of Occupants	Renski et al. (1999); Oh (2006)
Speed Limit	Renski et al. (1999); Khattak et al. (2002); Oh (2006); Gårder (2006); Malyshkina and Mannering (2010); Savolainen and Ghosh (2008); Haleem and Abdel-Aty (2010); Zhu and Srinivasan (2011); Yasmin and Eluru (2013)
Light Conditions	Klop and Khattak (1999); Rifatt and Tay (2009); Wang et al. (2009); Haleem and Abdel-Aty (2010); Khattak et al. (2002)
Weather Conditions	Khattak et al. (1998); Abdel-Aty (2003); Wang et al. (2009)
Road Conditions & Characteristics	Khattak et al. (1998); Krull et al. (2000); Lu et al. (2006); Rifatt and Tay (2009); Quddus et al. (2010); Zhu and Srinivasan (2011)
Contributing Circumstances	Chang and Wang (2006); Bernard and Sweeney (2015)

Many researchers have reported age as a significant factor in influencing crash severity (Delen et al. 2006; Kuhnert et al. 2000). Khattak and Rocha (2003) found that young drivers increase the risk of higher injury severity in single-vehicle crashes, while others have suggested that older drivers have higher risks of severe injury, given a crash occurence (Abdelwahab and Abdel-Aty 2002; Bédard et al. 2002; Abdel-Aty 2003; Schneider et al. 2009; Rifaat et al. 2011; Yasmin and Eluru 2013).

Chang and Wang (2006) found that contributing circumstances and driver actions are critical in determining crash severity. Studies reported that passenger presence increases the risk of injury (Savolainen and Ghosh 2008; Schneider et al. 2009), severity increases as the number of vehicle passengers increase (Renski et al. 1999; Oh 2006), and distracted drivers have a higher risk of greater severity (Zhu and Srinivasan 2011).

Many studies also reported that alcohol presence significantly increases the risk of severe injury (Khattak et al. 1998; Renski et al. 1999; Krull et al., 2000; Bédard et al. 2002; Khattak et al. 2002; Kockelman and Kweon 2002; Abdel-Aty 2003; Zajac and Ivan 2003; Donnell and Mason 2004; Delen et. al 2006; Rifaat and Tay 2009; Schneider et al. 2009; Wang et al. 2009; Moudon et al. 2011; Yasmin and Eluru 2013) and fatality (Islam and Mannering 2006; Rifaat et al. 2011). And driving at speeds too fast for conditions (Bédard et al. 2002; Rifaat and Tay 2009), speeding (Khattak et al. 1998; Khattak and Rocha 2003; Schneider et al. 2009), and higher speed limits (Renski et al. 1999; Khattak et al. 2002; Oh 2006; Gårder 2006; Malyshkina and Mannering 2010; Savolainen and Ghosh, 2008; Haleem and Abdel-Aty 2010; Zhu and Srinivasan 2011; Yasmin and Eluru, 2013) significantly increase the risk of severe injury. Importantly, results revealed that the interaction between higher speed limits and alcohol increase the risk of crash severity (Yan and Radwan 2006; Eustace et al. 2014).

Wang et al. (2009) found that favorable weather decreases crash severity and Abdel-Aty (2003) reported that adverse weather increases severity. Yet, Khattak et al. (1998) found adverse weather to significantly decrease the risk of severe injury for crashes; and Delen et al. (2006) indicated that weather conditions are not influential in crash severity. Lu et al. (2006) claimed that road condition has the greatest influence on crash severity; however, Jiang et al. (2013) concluded that improved road quality does not essentially reduce injury severity. Khattak et al. (1998), Rifaat and Tay (2009), and Quddus et al. (2010) reported that wet/slippery road surface decreases the risk of severe injury; yet, Krull et al. (2000) and Zhu and Srinivasan (2011) found that dry surfaces increase the risk of severity. Finally, studies reported that dark, unlit conditions increase crash severity (Klop and Khattak 1999; Rifaat and Tay 2009; Haleem and Abdel-Aty 2010), favorable lighting conditions decrease severity at freeway diverge areas (Wang et al. 2009), dusk (over dark) conditions reduce the risk of severe injury at unsignalized intersections (Haleem and Abdel-Aty 2010), and darkness increases the risk of greater injury severity for older drivers (Khattak et al. 2002).

To build upon prior research, two decision tree models are estimated and compared to examine the effect of and intricate relationships among suggested explanatory variables, to provide a context for understanding the relative reduction in overall risks associated with reducing the frequency of driver behaviors that contribute to the likelihood of different crash severity outcomes, and to provide better information for transportation policy that will enhance transportation safety efforts.

DATA

The Missouri State Highway Patrol Traffic Division collects and preserves crash report data, and codes and classifies the reports for entry into the Statewide Traffic Accident Records System (STARS) database (Missouri State Highway Patrol 2012). This study uses three relevant datasets from the STARS database: accident level data, vehicle level data and personal level data, and the years 2002 to 2012 are combined into a single dataset containing 3,902,742 observations. When considering motor vehicle drivers with a Missouri issued driver's license who contributed to a reported crash, cross tabulation results identify 1,264,905 observations in the dataset with the crash severity distributed as 0.6% fatal, 28.1% injury, and 71.3% property damage only. The explanatory variables included in this analysis are presented in Table 2.

Table 2: Explanatory Variables Included in the Analysis

Driver Characteristics	**Categorical Variable**
Age	Young (<21 years-old); Middle (≥21 and <55 years-old); Mature (≥ 55 years-old); Unknown
Gender	Male; Female; Unknown
Vehicle Occupants	**Numerical Variable**
Total Number of Occupants	1 to 149
Contributing Circumstances	**Binary Variable**
Alcohol	Present = 1; Not Present = 0
Animal(s) in Roadway	Present = 1; Not Present = 0
Distracted/Inattention	Present = 1; Not Present = 0
Drugs	Present = 1; Not Present = 0
Failed to Yield	Present = 1; Not Present = 0
Following Too Close	Present = 1; Not Present = 0
Improper Backing	Present = 1; Not Present = 0
Improper Lane Usage/Change	Present = 1; Not Present = 0
Improper Passing	Present = 1; Not Present = 0
Improper Turn	Present = 1; Not Present = 0
Improperly Stopped	Present = 1; Not Present = 0
Other[1]	Present = 1; Not Present = 0
Overcorrected	Present = 1; Not Present = 0
Physical Impairment	Present = 1; Not Present = 0
Speed - Exceeds Limit	Present = 1; Not Present = 0
Too Fast for Conditions	Present = 1; Not Present = 0
Vehicle Defects	Present = 1; Not Present = 0
Violation Stop Sign/Signal	Present = 1; Not Present = 0
Vision Obstructed	Present = 1; Not Present = 0
Wrong Side - Not Passing	Present = 1; Not Present = 0
Wrong Way (One Way)	Present = 1; Not Present = 0
Location	**Categorical Variable**
Crash Location	On Roadway; Off Roadway
Road Characteristics	**Categorical Variable**
Road Conditions	Other/Unknown; Wet; Snow; Ice: Dry
Road Alignment	Unknown; Curve; Straight
Road Profile	Unknown; Hill/Grade; Crest; Level
Road Surface	Unknown; Asphalt; Gravel; Brick/Dirt/Sand/Multi-Surface, Concrete
Speed Limit	15 or 20mph; 25 or 30mph; 35 or 40mph; 45 or 50mph; 55 or 60mph; 65 or 70mph; Unknown

(Table 2 continued)

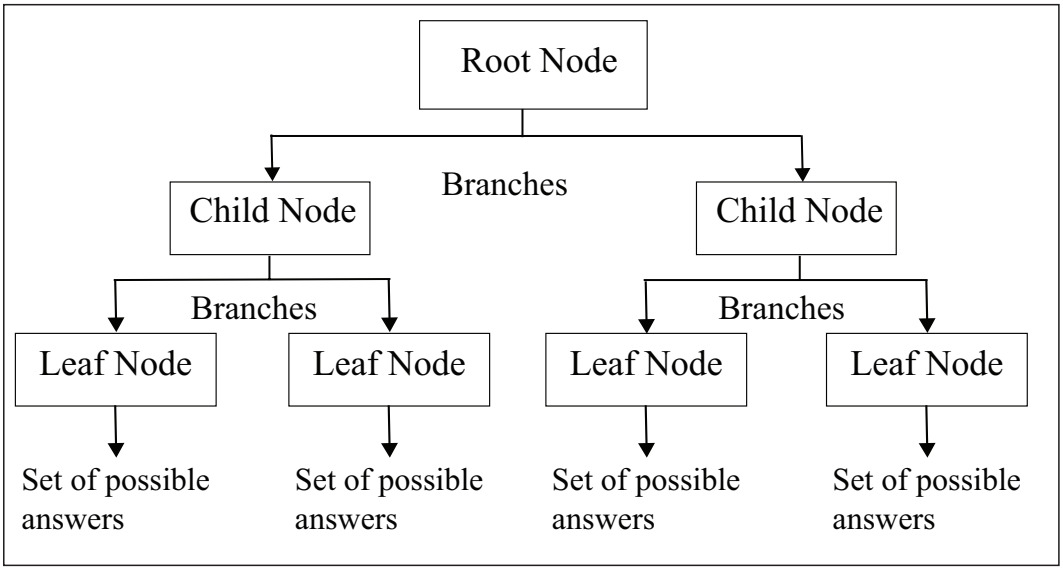
Environmental Factors	**Categorical Variable**
Weather Conditions	Cloudy; Rain; Snow; Sleet; Freezing Rain; Fog/Mist; Indeterminate; Clear
Light Conditions	Indeterminate; Dark-Streetlights On; Dark-Streetlights Off; Dark-No Streetlights; Daylight
Dependent Variable	**Categorical Variable**
Injury Severity	Fatal; Injury; Property Damage Only

Initial model runs suggested quasi-separation, which was resolved by combining the following variables with similar magnitudes into the *Other* variable: *Improper Signal*, *Improper Start from Park*, *Improperly Parked*, *Driver Fatigue/Asleep*, *Failed to Dim Lights*, *Failed to Use Lights*, *Improper Towing/Pushing*, *Improper Riding/Clinging to the Vehicle Exterior*, *Failed to Secure Load/Improper Loading*, *Object/Obstruction in the Roadway*.

METHODOLOGY

Decision tree models may be used for classification of occurrences into pre-specified groups, prediction of values of a dependent variable based on values of independent variables, and data exploration in model building. The tree is built by applying decision rules sequentially that split a larger heterogeneous population into smaller more homogeneous subsets (termed nodes) based on the single, most predictive input factor (Eustace et al. 2014) as illustrated in Figure 1 (Bayam et al. 2005). Subset purity is measured and evaluated to determine the best split for the subset (Mingers 1989b), and factors deemed statistically homogenous, with respect to the target outcome, are combined (Trnka 2010). Splitting continues for each node until no more splits are possible or until pre-defined stopping parameters (e.g., maximum tree depth or minimum number of records in branch) are reached.

Figure 1: Structure of a Decision Tree (Bayam et al. 2005)



Decision trees have several advantages over other models including the following: nonlinear relationships between variables do not affect performance; the data partitioning yields insights into input/output relationships; each path of the decision tree contains an estimated risk factor; missing values are accommodated automatically; and the output is simple to understand and interpret (Bernard Bracy 2017). However, overfitting of the model can occur if the learning algorithm fits data that are irrelevant, resulting in a model that may not be generalizable (Bayam et al. 2005). To avoid overfitting and improve generalization, pruning may be used to remove lower-level splits that do not significantly contribute to the generalized accuracy of the model (Mingers 1989a).

Decision tree algorithms, including CART and CHAID, build and prune decision trees in different ways. CART creates binary trees by splitting records at each node, and builds larger trees that are pruned back to mitigate overfitting of the model. CHAID creates wider, non-binary trees (often with many terminal nodes connected to a single branch) and automatically prunes the decision tree to avoid overfitting (Bayam et al. 2005).

Both CART and CHAID trees are estimated, the discriminatory performance of each algorithm is evaluated, and the model with the greatest discriminatory power is identified. The models' performances are compared by calculating and evaluating the classification accuracy and the area under the ROC curve (AUC) values for each model. The dataset is randomly partitioned into a training set (75%) to estimate the model and a testing set (25%) to assess model classification accuracy, and partitioning was completed prior to estimating both models so that identical observations are used. Classification accuracy for each category of the outcome variable is determined by dividing the number of predicted outcomes by the number of observed outcomes (as illustrated in Tables 3 and 4). IBM SPSS 22.0 and IBM SPSS Modeler 15.0 are used to estimate the decision tree models.

The CART methodology employs the algorithm proposed by Breiman et al. (1984), where nodal splitting criteria are set to a minimum value of 100 records in a parent branch and a minimum of 50 records in a child branch as the stopping criteria. The Gini coefficient is used as the impurity measure for the categorical targets, the maximum tree depth is set to 15 branches, and the tree is pruned by merging leaves on the same branch using a value of one as the maximum difference in risk in standard errors. The resulting CART decision tree model finds 23 variables significant, includes 948,679 observations in the training set and 316,784 in the testing set, and results in a classification accuracy of 72.32% and 72.30% for the training set and the testing set, respectively.

The CART classification accuracy for the training set is determined by dividing the number of severity outcomes predicted by the model by the total observed severity outcomes in the testing set. As illustrated in Table 3, the model correctly classified 12.6% of injury outcomes, determined by dividing 33,743 by 268,465 (0+33,743+234,722); and correctly classified 96.8% of property damage outcomes, calculated by dividing 652,654 by 674,191 (0+21,837+652,354). The overall percent correct for the training set, 72.32%, is found by summing the total occurrences of the predicted fatal and observed fatal outcomes (0), the predicted injury and observed injury outcomes (33,743), and the predicted property damage and observed property damage outcomes (652,354), and then dividing by the number of observations in the testing set (948,679).

Table 3: CART Classification Accuracy for the Training Set

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	0	1,760	4,263	0.0%
Injury	0	33,743	234,722	12.6%
Property Damage	0	21.837	652,354	96.8%
Overall Percentage	0.0%	6.0%	94.0%	72.32%

The CHAID methodology employs the algorithm proposed by Kass (1980), where nodal splitting criteria are set to a minimum value of 100 records in a parent branch and a minimum of 50 records in a child branch, and the maximum tree depth is set to 15 branches. The Pearson measure is used as the chi-square measure to test for independence for categorical targets, and the significance level for both splitting and merging is set to 0.05. The final estimated CHAID decision tree model suggests 30 variables are significant, includes 948,679 observations in the training set and 316,784 in the testing set, and results in a classification accuracy of 73.06% and 73.00% for the training set and the testing set, respectively.

The CHAID classification accuracy for the training set, illustrated in Table 4, is also determined by dividing the number of severity outcomes predicted by the model by the total observed severity outcomes in the testing set. The model correctly classified 23.6% of injury outcomes, determined by dividing 63,279 by 268,465 (0+63,279+205,186); and correctly classified 93.4% of property damage outcomes, calculated by dividing 629,793 by 674,191 (0+44,398+629,793). The overall percent correct for the training set, 73.06%, is found by summing the total occurrences of the predicted fatal and observed fatal outcomes (0), the predicted injury and observed injury outcomes (63,279), and the predicted property damage and observed property damage outcomes (629,793), and then dividing by the number of observations in the testing set (948,679).

Table 4: CHAID Classification Accuracy for the Testing Set

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	0	3,175	2,848	0.0%
Injury	0	63,279	205,186	23.6%
Property Damage	0	44,398	629,793	93.4%
Overall Percentage	0.0%	11.7%	88.3%	73.06%

The AUC is a widely recognized measure of discriminatory power (Worster et al. 2006) and quality of probabilistic classifiers (Vuk and Curk 2006), which measures the classifiers' performance across the entire range of potential outcome distributions (Vuk and Curk 2006), and is equal to the probability that a classifier will rate a randomly chosen positive outcome higher than a randomly chosen negative outcome (Fawcett 2006). The AUC values are determined by calculating the area under the ROC curves, which are constructed by plotting the true positive rate against a false positive rate for subsets of the observations (Fawcett 2006). The AUC results for the CART and CHAID's capabilities to predict a fatal outcome relative to non-fatal outcomes and to predict a property damage only outcome relative to injury outcomes are presented in Table 5.

Table 5: Accuracy Comparison of CHAID and CART Models

Decision Tree Approach	Classification Accuracy Training Set	Classification Accuracy Testing Set	AUC Value Fatal vs. Nonfatal Training Set	AUC Value Fatal vs. Nonfatal Testing Set	AUC Value Non-injury vs. Injury Training Set	AUC Value Non-injury vs. Injury Testing Set
CHAID	73.06%	73.00%	0.899	0.898	0.717	0.717
CART	72.32%	72.30%	0.759	0.761	0.667	0.667

The AUC values are compared to determine if there is a significant difference between the models' abilities to predict (1) a fatal outcome relative to property damage and injury only outcomes and (2) a property damage only outcome relative to fatal and injury outcomes by calculating a

critical ratio *z*, defined by Hanley and McNeil (1983). A statistically significant difference between the models' ability to predict a fatal outcome relative to a non-fatal outcome is not found ($z = 0.38$; $p = 0.35197$); yet, a statistically significant difference between the models' ability to predict a property damage only outcome relative to an injury or fatal outcome does exist ($z = 77.15$; $p = <0.00001$).

Because of its greater classification accuracy and higher AUC values, as illustrated in Table 5, the CHAID model better discriminates than the CART model between crash severity outcomes and is carried forward to compare findings here to prior literature findings and to examine current Missouri driving rule and policy implications.

ANALYSIS AND RESULTS

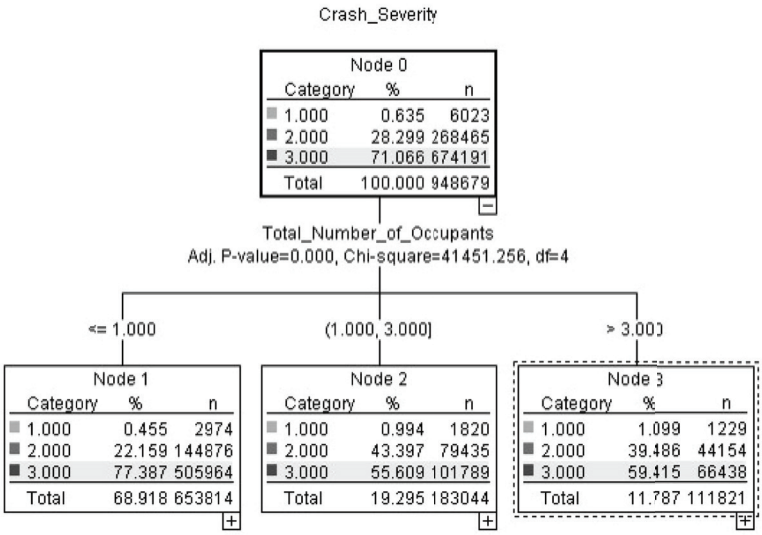
The factors with the greatest predictor importance for crash severity (i.e., the relative importance of each predictor in estimating the model) are calculated using the CHAID model results. The model determines predictor importance by computing the reduction in variance of the target attributable to each predictor via a sensitivity analysis (Saltelli 2002; Saltelli et al. 2004). The estimated CHAID tree identifies the factors with the greatest predictor importance for crash severity as total number of occupants, speed limit, speeds that exceed the limit, alcohol, failed to yield, violation of a stop sign or signal, physical impairment, driving on the wrong side of the road when not passing, crash location, and improper backing. To illustrate the insights afforded by the estimated CHAID decision tree and to provide a context within which to evaluate reductions in motor vehicle crash risk, decision rules focusing on the variables with the greatest predictor importance in the CHAID model are examined.

Number of Occupants

The CHAID model identifies *total number of occupants* as the best predictor to form the first branch of the decision tree, since it has the greatest importance in estimating the model and partitions the training set into three branches characterized as single occupant, two or three occupants, or more than three occupants. Findings suggest that as the total number of occupants involved in a crash increase, so does the probability that a fatal outcome will occur. This result is consistent with prior research findings that crash severity probabilities increase as the number of vehicle passengers increase (Renski et al. 1999; Oh 2006).

As illustrated in Figure 2, the probability that a fatal outcome (Category 1) will occur increases as the number of occupants involved in the crash increases: 0.455% for single occupant crashes, 0.994% for crashes involving two or three occupants, and 1.099% for crashes involving more than three occupants. Interestingly, the probability that an injury outcome (Category 2) will occur does not necessarily increase as the number of occupants increases. When increasing the total number of occupants from a single occupant to two or three occupants, the likelihood of an injury outcome increases from 22.159% to 43.397%; yet, when increasing the number of occupants to more than three occupants, the likelihood of an injury outcome decreases to 39.486%. Both findings indicate nonlinearity, and illustrate the importance of using the CHAID decision tree for analysis of non-linear effects.

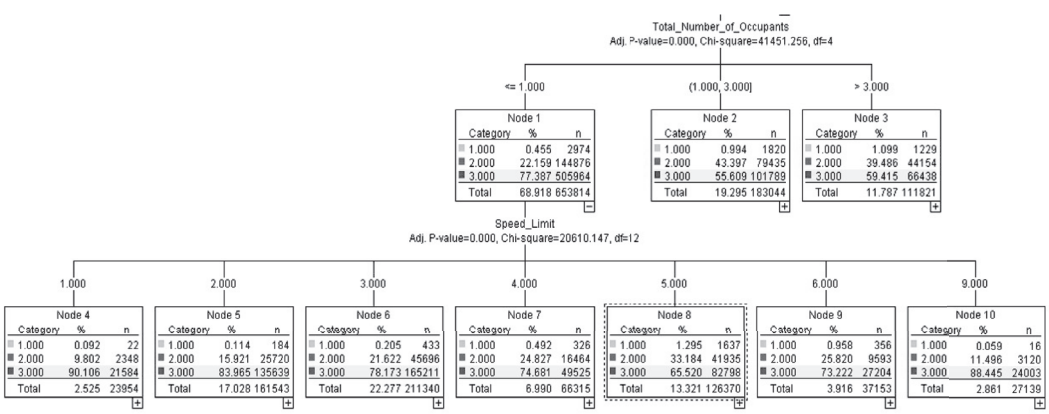
Figure 2: First Branch of CHAID Tree – Total Number of Occupants



Speed Limit

The CHAID model identifies speed limit as the second most important predictor variable, and serves as the second branch for single occupant crashes. As illustrated in Figure 3, the probability of a fatal or injury outcome increases for speed limit zones of up to 55 mph and 60 mph for single occupant crashes. Yet, as model results suggest, a change from 55mph and 60 mph to 65 mph and 70 mph decreases the likelihood that the outcome will be fatal or injurious, which could be attributed to the type of roads in which this speed limit is typically present in Missouri (e.g., interstates). This finding further solidifies the importance of using CHAID decision trees to analyze non-linear effects.

Figure 3: Single Occupant Crash Branch Two – Speed Limit



Zone 1 = 05 mph and 20 mph; zone 2 = 25 mph and 30 mph; zone 3 = 35 mph and 40 mph; zone 4 = 45 mph and 50 mph; zone 5 = 55 mph and 60 mph; zone 6 = 65 mph and 70 mph; and zone 9 = Unknown

This study's results also are consistent with previous research findings that higher speed limits significantly increase the risk of severe injury outcomes (Renski et al. 1999; Khattak et al. 2002; Oh 2006; Gårder 2006; Malyshkina and Mannering 2010; Savolainen and Ghosh 2008; Haleem and Abdel-Aty 2010; Zhu and Srinivasan 2011; Yasmin and Eluru 2013).

Speeds - Exceed Limit

Crashes involving driving at speeds that exceed the posted limit are more likely to cause fatal and injury outcomes for each partition of the number of occupants. For single occupant crashes, model results indicate that driving at speeds that exceed the limit in zones of 35 mph or 40 mph and 65 mph or 70 mph increases the chance of a fatal outcome from 0.133% to 3.689% and from 0.760% to 4.746%, respectively. For crashes with two or three occupants, additional results suggest that driving at speeds that exceed the limit in zones of 35 mph or 40 mph and 45 mph or 50 mph increases the chance of a fatal outcome from 0.233% to 4.671% and 0.568% to 6.534% respectively. Finally, for crashes with more than three occupants, driving at speeds that exceed the limit increases the chance of a fatal outcome occurring as speed limit zones increase: 25 mph or 30 mph equals 3.409%; 35 mph or 40 mph equals 6.902%; 45 mph or 50 mph equals 8.543%; 65 mph or 70 mph equals 13.223%. These findings, which suggest that driving at speeds that exceed the limit have a greater risk of injury, are consistent with prior research (Khattak et al. 1998; Renski et al. 1999; Khattak et al. 2002; Khattak and Rocha 2003; Gårder 2006; Oh, 2006; Savolainen and Ghosh 2008; Schneider et al. 2009; Haleem and Abdel-Aty 2010; Malyshkina and Mannering 2010; Zhu and Srinivasan 2011; Yasmin and Eluru 2013).

Importantly, this study identifies interactions between speeding and other circumstances. For example, for single occupant crashes, results indicate that a young driver (under the age of 21) driving at speeds that exceed the limit in a speed limit zone of 25 mph to 30 mph and 65 mph to 75 mph has a lesser chance of a fatal outcome (0.676% and 3.049%) than older drivers (2.063% and 1.105%, respectively for middle aged drivers and mature drivers in 25 mph/30 mph zones and 5.714% for both older groups in 65 mph/75 mph zones). For crashes with two or three occupants, driving at speeds that exceed the limit in a speed zone of 35 mph or 45 mph during dark, but lit conditions increase the likelihood of a fatal outcome from 2.607% to 8.108%, yet decreases the likelihood of an injury outcome of 70.142% to 66.366% when compared with driving at speeds that exceed the limit during other lighting conditions. Additionally, for two or three occupant crashes, males driving at speeds that exceed the posted limit of 45 mph or 50 mph have a greater chance of a fatal outcome (7.950%) relative to their female counterparts (1.010%). Finally, for crashes involving two or three occupants, a 20.870% chance of a fatal outcome and a 68.216% of an injury outcome results when driving at speeds that exceed the limit while under the influence of alcohol.

Alcohol

Crashes that occur while driving under the influence of alcohol have greater crash severity regardless of the number of occupants involved in the crash, as supported by prior literature; yet, this study shows that its importance is more prevalent for crashes involving multiple occupants. The presence of alcohol represents the second split in the decision tree for two and three occupant crashes, and model results show that alcohol presence increases the probability of a fatal outcome and an injury outcome from 0.778% to 5.175% and 42.411% to 62.486%, respectively, and for more than three occupant crashes, where alcohol presence increases the probability of a fatal outcome and an injury outcome from 0.856% to 7.023% and 38.676% to 59.273%, respectively.

Additionally, results reveal dangerous interaction effects between alcohol and other variables. For example, for single occupant crashes, driving under the influence of alcohol in a speed limit zone of 65,mph or 70,mph increases the probability of a fatal outcome from 0.820% to 3.053%

and of an injury outcome from 24.742% to 42.215%, compared with similar circumstances when alcohol is not present. When adding speeding to alcohol use at such high speeds, the risk of a fatal outcome and an injury outcome increases to 6.024% and 56.024%, respectively.

For crashes involving two or three occupants, results suggest that a crash occurring when alcohol is present increases the probability of a fatal outcome from 0.763% to 5.181% and the probability of an injury outcome from 42.380% to 62.327% compared with crashes when alcohol is not present. Moreover, adding speeding when on a hill or a crest to this scenario increases the probability of a fatal outcome and injury outcome to 20.882% and 65.429% respectively.

When a crash involves three or more occupants, the probability of a fatal outcome increases from 0.866% to 7.103% and an injury outcome increases from 38.752% to 60.276% when alcohol is present; when speeding is included, the chance of a fatal and an injury outcome increases to 17.221% and 65.558%, respectively. Finally, when adding a dark light condition (with no streetlights or streetlights off) to this scenario, the chance of a fatal outcome increases to 26.627%, and an injury outcome increases to 62.130%.

Failing to Yield

Crashes involving failing to yield are also more likely to cause severe outcomes, as confirmed by prior research (Peek-Asa et al. 2010), and failure to yield has important interaction effects with other characteristics. For instance, when failing to yield is present and a single occupant on-roadway crash in a speed limit zone of 65,mph or 70,mph occurs, model results indicate that the chance of a fatal or injury outcome increases from 0.471% and 19.260% to 0.972% and 25.791%, respectively, than if failing to yield is not present. For crashes with two or three occupants, drivers who fail to yield in a speed limit zone of 65,mph or 70,mph have a greater chance of a fatal outcome (4.708%) and injury outcome (53.861%) than if the driver yielded properly.

DISCUSSION

To provide a context for understanding the relative reduction in overall risks associated with reducing the frequency of driver behaviors that contribute to the likelihood of different crash severity outcomes, historic outcomes are examined to determine annual upper and lower bounds on the changes in the number of drivers involved in fatal, injury, or property damage only crashes if selected contributory circumstances might be individually eliminated. The analysis provides a context in which to employ counterfactual arguments to provide reasonable bounds on how the total number of crash severity outcomes might change with measures designed to reduce the frequency of occurrence of the significant contributing factors. The annual bounds are calculated for each severity outcome by dividing the number of outcomes by the number of effective years multiplied by the proportion of the training set (11 * 0.75).

Considering the contributing circumstances that have the greatest predictor importance for severe crash outcomes, lower and upper bounds for changes in the annual number of drivers involved in each of the three severity outcomes are determined by 1) removing the contributing circumstance for each driver and assuming the crash still occurs with severity outcome probabilities now determined by the outcome probabilities of the complementary node (a ceteris paribus lower bound) and 2) removing the contributing circumstance and alternatively assuming that the driver is not involved in a crash at all (an upper bound). This bounding technique presumes that no casual relationships exist among contributing circumstances in estimating the lower bounds and, alternatively, that the removed contributing circumstance was solely responsible for causing the accidents in estimating the upper bounds.

Table 6 presents the lower and upper bounds of the reductions in the annual numbers of drivers involved in fatalities, injury, and property damage outcomes associated with the six most

important contributing circumstances. As illustrated in Table 6, the elimination of the specific contributing circumstance clearly changes the distribution of the number of drivers involved in the three outcomes. For example, alcohol involvement has significant detrimental effects on the number of Missouri drivers involved in fatal outcomes. When eliminating alcohol as a contributing circumstance and assuming the crash then does not occur, 191 fewer annual driver contributions towards fatal crashes might be prevented. When eliminating alcohol as a contributing circumstance and assuming the crash still does occur, the estimated severity outcomes are redistributed and at least 135 fatal accident outcomes per year might be avoided.

Table 6: Estimated Annual Reductions in the Number of Drivers Involved in Each Severity Outcome if a Contributing Circumstance is Eliminated

	Fatal		Injury		Property Damage Only		N[1]
Contributing Circumstance	Est Lower Bound	Est Upper Bound	Est Lower Bound	Est Upper Bound	Est Lower Bound[2]	Est Upper Bound	
Speed - Exceed Limit	107	133	477	1,344	-801	1,325	2,802
Alcohol	135	191	841	2,741	-1,418	3,187	6,119
Failed to Yield	43	88	1412	6,779	-1,455	15,268	22,135
Violation - Stop Sign/Signal	16	39	692	2,133	-708	2,956	5,128
Wrong-Side	67	110	157	1,065	-224	1,212	2,388
Physical Impairment	11	36	427	1,215	-437	1,190	2,442

[1]N = Number of estimated cases per year and equal to the sum of the estimated upper bounds.
[2]A negative value for property damage only outcome represents an increase for the least severe outcome, given the assumption that the crash still occurs.

Still, the interaction effects of variables identified by the CHAID model are important when analyzing crash severity data. For example, it is readily discovered that driving while under the influence of alcohol, driving at speeds that exceed the limit, failing to yield, driving on the wrong side of the road, violating a stop sign or signal, and driving while physically impaired lead to a significant number of fatalities each year in Missouri. The effect of these factors on the probability of a severe outcome is dependent upon other variables, including the number of vehicle occupants involved in the crash, the speed limit, actual driving speed, lighting conditions and driver's age. Thus, this study concludes that policy makers should consider the interaction of driver related contributory circumstances and other conditions when formulating future legislation intended to reduce the number of fatal outcomes.

CONCLUSIONS

Key findings presented in the analysis have important implications for possible changes in the current Missouri Driver Guide - Rules of the Road (Missouri Department of Revenue 2014). Drawing upon these findings, policy recommendations are identified and discussed for the contributing circumstances that greatly increase the likelihood of more severe outcomes of motor vehicle crashes: speed limit, driving at speeds that exceed the limit, and alcohol use.

Speed Limit/Speed - Exceed Limit

The Missouri Driver Guide states, "Speed limit signs indicate the maximum speed allowed by law, and do not mean that all parts of the road can be safely driven at those speeds under all conditions. The speed limit is the maximum allowable speed in ideal conditions" (Missouri Department of Revenue 2014, p. 37); and it is recommended that driving speed be adjusted as appropriate for changes in road conditions and characteristics, visibilities, other road users, and weather conditions. As previously suggested, the interaction of speed limit and driving at speeds that exceed the limit increase the likely severity of crash outcomes, which is confirmed by the statements made. For example, driving at speeds that exceed the posted limit of 35 mph to 45 mph during dark, but lit conditions have an increased likelihood of a fatal outcome than when speeding during other lighting conditions. As a result, it is recommended that patrol units be aware that dark conditions increase the probability of severe outcomes and adjust accordingly.

Additionally, the likelihood of a fatal crash is higher when driving on the wrong side of the road in speed limit zones of 45 mph to 60 mph and when failing to yield in a speed limit zone of 65 mph or 70 mph than if these contributing circumstances are not present. Following successful application in North Carolina and California, many states have adopted innovative strategies to reduce wrong-way driving, such as lowering the height of "Do Not Enter" and "Wrong Way" signs, increasing the size of signage, locating signage on both sides of the exit travel lane, changing lighting and minor ramp geometrics, and illuminating "Wrong Way" signs that flash when a wrong-way vehicle is detected (Zhou and Rouholamin 2014). As a result, the study may infer that in higher speed limit zones, preventive measures to reduce driving on the wrong side of the road and failing to yield, such as prominent signage, are of great importance.

Alcohol

Driver alcohol use is one of the most significant predictors of crash severity. Currently under Missouri law, drivers who are found guilty of driving while intoxicated (DWI) may be subject to paying a fine, having his/her license revoked, or being imprisoned (Missouri Department of Revenue 2014). Moreover, if someone is injured or killed because of driving under the influence of alcohol, the driver may "spend two to seven years in jail, pay a $5,000 fine, and/or lose your driver license for five years" (Missouri Department of Revenue 2014 p.77). Because of the large increase in the probabilities of injury and fatal outcomes when driving under the influence of alcohol, these laws may not be stringent enough in the prevention of drinking and driving given the clear large increase in the likelihood of severe outcomes. Additionally, Missouri law currently requires any person guilty of a second alcohol intoxication-related traffic offense to install an ignition interlock device on all vehicles operated by the offender before reinstating driving privileges (Missouri Department of Transportation 2013). Since drivers with a blood alcohol concentration above the legal limit that are involved in fatal crashes are six times more likely to have a prior DWI conviction (U.S. Department of Transportation (2014), to deter multiple offenses from occurring, all DWI first-time offenders could be required to use ignition interlocks.

Research suggests that injuries and fatalities from impaired driving can be prevented through community-based approaches (DeJong and Hingson 1998; Holder et al. 2000; Shults et al. 2009). The Missouri Department of Revenue encourages such approaches through reporting drunk drivers by calling 911 and providing law enforcement with the license plate number of the vehicle, a physical description of the car and driver, and the vehicle's location (Missouri Department of Revenue 2014). However, to reduce the number of DWI drivers on Missouri roadways, this study recommends that this process be simplified and that a hotline and/or web-notification mechanism be considered (with possible rewards) for reporting DWIs.

To further reduce DWIs, Missouri law enforcement agencies implement sobriety checkpoints at temporary, random locations (Reynolds 1989). Research indicates that high-profile enforcement efforts, specifically frequent sobriety checkpoints, are effective in reducing alcohol-related fatal crashes (Elder et al. 2002), and recent studies found such checkpoints reduce the number of fatal outcomes by 20% (Shults et al. 2009). As described earlier, a strong interaction is found between high speed limits, alcohol intoxication, and crash severity. As a result, this study recommends that future DWI checkpoints might be located at on-ramps to high speed highways and interstates to reduce the number of intoxicated drivers driving at high speeds.

LIMITATIONS AND FUTURE RESEARCH

Limitations to this research exist and may be resolved through future research endeavors. First, this study considers data compiled from the entire state of Missouri, and the general findings may not be appropriate in specific differentiated locations throughout the state. Future research may address this limitation by partitioning data into smaller regions of Missouri (urban, rural, suburban, county, zip code, and other meaningful partitions) and by examining regional factors and their effect on injury severity to contribute to more localized legislation. Second, this study considers only Missouri data. Future research may apply the same methodological approach to additional state crash datasets to assess policy implications for various locations. Third, additional or alternate variables may be considered in future research to examine other factors that may contribute differentially to crash severity. These include variables such as seasonality, peak driving times, highway class, rural versus urban location, crash type, and vehicle type. Additionally, future studies may compare the decision tree models to other methodological approaches, such as multinomial logit and ordinal logit and probit models. Finally, future research may apply the methodological techniques presented here to other modes of transportation and assess safety measures, risk, and disruptions beyond roadways.

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Stochastic Modeling of the Last Mile Problem for Delivery Fleet Planning

by Jay R. Brown and Alfred L. Guiffrida

This paper presents a stochastic representation of the last mile problem that quantifies expected maintenance, regular labor, overtime labor, fuel, and carbon emission costs resulting from different delivery fleet options. The last mile delivery fleet planning model presented herein can be used in a decision framework to evaluate alternative delivery strategies involving fleet size and delivery frequency with information regarding cost, carbon emissions, service levels for available delivery hours, and payload capacity, as well as the transportation capacity needed to meet customer demand and lends itself well to performing what-if analyses.

INTRODUCTION

Environmental concerns are impacting how organizations design, coordinate, and manage their supply chains, and have generated a huge interest in the topic of green supply chain management (Gurtu et al. 2017; Das and Posinasetti 2015; Fahimnia et al. 2015). Srivastava (2007) defines green supply chain management (GSCM) as the integration of environmental thinking into supply chain management. For a gateway into the GSCM literature, the reader is referred to the review articles contributed by Shibin et al. (2016), Wong et al. (2015), Min and Kim (2012), and Sarkis et al. (2011). Managerial interest in GSCM practices is found in a wide cross section of industries. The global scope of this interest is illustrated by recent case study research on GSCM in the construction industry in the United Arab Emirates (Balasubramanian and Sundarakani 2017), meat processing in Italy (Sgarbossa and Russo 2017), mining in Ghana (Kusi-Sarpong et al. 2016), heavy equipment manufacturing in India (Gandhi et al. 2015), rubber processing in Indonesia (Darmawan et al. 2014), and automobile manufacturing in Korea (Lee 2011).

In a climate of enhanced awareness of environmentally sustainable business practices, greater pressure is being placed on organizations to advance sustainable logistics within the operation of their supply chains (Abbasi and Nilsson 2016; Björklund et al. 2016; Golicic et al. 2010). Comprehensive reviews of sustainable logistics have been conducted for various modes of freight transportation, including roadways (Demir et al. 2014), railways (Aditjandra et al. 2016), maritime (Davarzani et al. 2015), air (Teoh and Khoo 2016), and intermodal (Roso 2013). The carbon footprint associated with freight transport across all modes is rapidly becoming a key managerial concern and is especially prevalent in road transportation by transport vehicles in North America and Europe.

The last mile problem (LMP) implies making deliveries from the location (depot/warehouse/transportation hub) where products are maintained in the supply chain to the home address or designated collection point requested by customers. The LMP is a key element of the order fulfillment process within the operation of a supply chain (Bromage 2001; Lee and Whang 2001). While logistics costs vary with population density, product type, package size, and package weight, last mile delivery has shown to incur the highest transportation costs in the supply chain (Chopra 2003). For example, Grackin (2014) reports that the last mile delivery cost for a blouse manufactured in Asia and then delivered and sold to a customer in the United States can range from $4-$11, approximately 28%-78% of the total transportation cost. Because of the increased number and complexity of making last mile deliveries, cost and carbon emissions are becoming critical

concerns of supply chain managers, and companies have identified that they can save substantial cost, time, and carbon emissions by optimizing last mile delivery.

As e-commerce continues to grow, a greater burden is placed on last mile delivery. Logistics systems, which were traditionally designed to accommodate a single lot delivery of multiple products from one business to another, are now under pressure to deliver high volumes of single parcels from a transportation/warehouse hub to multiple individual customers. With the global B2C (business to consumer) e-commerce market projected to reach $2.3 trillion by 2017, resolving last mile delivery issues will become a major customer service concern for firms (Khanna 2015). Millar (2015) comments that in addition to the cost of transportation, last mile home delivery presents additional managerial challenges as a result of invalid, incorrect, or hard to locate delivery addresses and unaccepted deliveries. Wygonik and Goodchild (2012) show that the routing and scheduling strategy plays a significant role in reducing emissions. The high costs associated with last mile delivery provide an opportunity for companies to achieve substantial cost and carbon emissions reductions through optimal planning and proper execution of a delivery plan.

Determining an optimal delivery fleet for dealing with the LMP, including the number of vehicles, available delivery hours, delivery range, and total freight capacity, is a problem with a solution that varies depending on the customer demand for that delivery cycle. If demand is high, more vehicles, more delivery time, or more freight capacity may be needed. On a day with less demand, the opposite is true. Demand for last mile delivery is typically not constant, and as a result, changes to the fleet operating characteristics may change from week to week or even from day to day. In this paper we present a stochastic model that can be used to aid decision makers in managing the operating characteristics of their vehicle delivery fleet in support of the LMP. The modeling framework is driven by stochastic customer demand and provides managers with metrics on service levels for on-time delivery, vehicle capacity, and driver labor hours. The last mile delivery fleet planning model presented herein can assist decision makers when dealing with uncertainties in delivery fleet planning and aid in finding the optimal delivery fleet strategy based on cost, carbon emissions, payload service level, and on-time delivery service level.

A distinguishing feature of the last mile delivery fleet planning model presented in this paper compared with other fleet models, is the stochastic modeling of travel distances for meeting customer demand in the last mile setting. The stochastic modeling of the LMP for delivery fleet planning allows for: 1) incorporating stochastic demand into the LMP in a varying multiple vehicle delivery environment, 2) incorporating carbon emissions that result from vehicle transportation into the LMP, and 3) the development of a planning model that incorporates uncertainty in terms of expected mileage and labor hours. By modeling LMP travel distances stochastically, the last mile delivery fleet planning model presented herein advances the literature since it improves the quality of information available to plan properly and enhances overall decision making due to the ability to gauge the probabilistic likelihood of the service level and costs associated with solving the LMP.

LITERATURE REVIEW

The development of the stochastic LMP model for delivery fleet planning presented herein draws upon the literature referred to in the operations research literature as "geometric probability" (Larson and Odoni 1981, Ch. 3). These models have been developed to determine the optimal distance traveled from a source (or set of sources) to customers in a geometric shaped demand region. These models can be broken down into two subgroups. Discrete models, which have known customer demand locations, seek to find the shortest total travel distance or most economical way to deliver goods to meet customer demand. With these discrete models, both demand at the known customer locations and travel distances for delivery routes between all locations are deterministic. Continuous models are characterized by a known amount of customer demand within a given demand region; however, the exact locations of the customers within the demand region are not known. Once the customer

demand locations within the demand region are populated, delivery routes with deterministic travel distances are established to service the customers. Customer demand is deterministic and the model seeks to determine an approximate total travel distance as a function of the characteristics of the demand region, such as size, geometric shape of the demand region, and the level of customer demand within the region (Beardwood et al. 1959; Newell 1973; Stein 1978; Daganzo 1984; Vaughan 1984; Jaillet 1988; Stone 1991). Route delivery distances can be measured using the Manhattan (L_1) metric, which implies only north, south, east, or west movements are allowed or the Euclidean (L_2) metric, which is direct point-to-point regardless of direction. The methodology used in these models has mostly been centered on approximating an average distance to tour all points as opposed to using the distribution of expected distance to capture the true stochastic nature of delivery by transport vehicle in the LMP. The distribution of expected distances is needed to provide management with a service-level-based decision tool for fleet management when meeting customer deliveries.

Langevin et al. (1996) provides a detailed review of the literature on continuous approximation models. These models approximate travel distance based on factors such as region size, shape, and number of deliveries. These models are attractive to supply chain analysts with respect to fleet planning for the LMP since distance is the key driver for evaluating vehicle delivery cost and capacity, determining delivery zones, and estimating the cost of the carbon footprint.

While not addressing the same fleet modeling characteristics and delivery problem found in the LMP, other models in the literature have provided functions for approximating the cost of serving customers under stochastic demand conditions. The research presented herein is not focused on the vehicle routing problem (VRP) since this research does not determine the specific routing of vehicles. The stochastic nature of this research provides an expected travel distance distribution based on the inputs. However, contributions from this area present similarities. The Lei et al. (2012) model can solve a combined vehicle routing and districting problem with stochastic customers. Carlsson et al. (2012) partition a geometric region to assign equitable workloads to vehicles for the stochastic vehicle routing problem.

The problem of optimizing a delivery fleet has been studied from many different perspectives. Jabali et al. (2012), while focused on a deterministic problem, present a continuous time approximation for fleet sizing that they embed in an optimization. Bent and Van Hentenryck (2004) consider the partially dynamic vehicle routing problem with time windows, where some customers are known for planning time while others are dynamic, with the goal of maximizing the number of customers served based on a fixed number of vehicles. Pillac et al. (2013) provide a review of dynamic VRPs that touches on stochastic modeling and vehicle fleet management.

Incorporating carbon emissions into decision-making has been an increasing area of recent interest in both research and practice. Glock and Kim (2015) studied a multiple-supplier-single-buyer supply chain that uses a heterogeneous vehicle fleet for transporting products and found that considering emission cost in the optimization problem may lead to different routing and production policies for the system. In a review of the literature on the LMP, Edwards et al. (2010) directly incorporate carbon emissions (CO_2) into the LMP. They introduce carbon footprint analysis to the LMP and compare the level of carbon emissions resulting from online versus conventional shopping for the non-food retail sector. Carbon emission from delivery vehicles was defined by the number of grams of CO_2 emitted per kilometer traveled, and the rate of emission was estimated based on secondary technical data sources of vehicle operation. Home deliveries and typical shopping trips were compared based on the aggregate gram weight of CO_2 generated during delivery. The findings suggest that home deliveries result in lower carbon emissions.

Zhang et al. (2015) present a low-carbon routing problem that merges the VRP with traditional costs and carbon emissions for a fixed fleet of delivery vehicles. Similar to the last mile delivery fleet planning model presented herein, carbon emission is calculated from travel distance, load, and speed. Soysal et al. (2014) develop a multi-objective linear programming (MOLP) model for a generic beef logistics network problem to minimize total logistics cost and secondarily minimize emissions from

transportation operations. Tang et al. (2015) show that reducing shipping frequency in a periodic inventory review system can reduce carbon emissions with a limited impact on total cost. Govindan et al. (2014) develop a model for simultaneously minimizing logistic costs and carbon emissions in a perishable two-echelon multiple-vehicle location-routing problem. Rigot-Muller et al. (2013) present optimization methods for minimizing total logistics-related carbon emissions for end-to-end supply chain distribution systems using Value Stream Mapping (VSM). These research articles demonstrate that while cost remains a key driver of behavior, reducing carbon emissions can be considered a complementary driver in many cases.

While similarities to certain aspects of this research exist in the literature, none have all the same characteristics. The research herein aims to increase the practicality of delivery fleet planning by creating a decision framework that includes a distribution of expected travel distance, probabilistic service levels, a carbon emissions component, and a multiple vehicle fleet of varying size. Much of the research involving stochastic demand only considers a single delivery vehicle (Ghiani et al. 2012) or rarely a fixed number of vehicles (Bent and Van Hentenryck 2004). Not having the ability to modify the size of the delivery fleet is a serious limitation that the research herein overcomes. Even week to week with changing demand, the ability to adjust the number of delivery vehicles can lower operational costs and improve customer service levels. A modeling environment that accommodates a multiple vehicle fleet of varying size delivering to ever-changing customers provides a greater range of decision options for management in satisfying customer demand.

STOCHASTIC LAST MILE MODEL DEVELOPMENT

Brown and Guiffrida (2014) introduced a stochastic last mile framework to model the distribution of expected travel distance based on the number of delivery vehicles, number of customers, and the size of the delivery region. The model assumes a circular demand region with a radius of R surrounding a centrally located depot as the starting point. Demand is considered to be uniformly and randomly distributed, which is supported in a review of continuous approximation models in freight distribution by Langevin et al. (1996). The number of delivery vehicles can vary from one to five vehicles, which results in the demand region being subdivided into T equally sized and shaped sub regions. Each sub region was assigned one vehicle; hence the number of sub regions equates directly with the number of individual delivery tours. Travel distance is measured in miles using the Manhattan (L_1) distance metric.

The expected distance traveled per day, μ_T, with standard deviation, σ_T, is a function of the radius of the demand region, R, the number of vehicles, T, and the number of nodes (customer delivery points plus the depot), N. Table 1 contains the formulas for quantifying the distribution of travel distances employed in this research. Brown and Guiffrida (2014) introduced these formulas in research to calculate the number of customers needed for a last mile delivery service to reach a carbon footprint break-even point with customer pick up. The research herein employs these formulas to capture expected travel distance, but from there a completely new model is introduced to create a decision framework for evaluating alternative delivery strategies involving fleet size and delivery frequency with information regarding cost, carbon emissions, and probabilistic service levels.

Table 1: Statistical Information of Model Equations

T	Mean			Standard Deviation		
	Equation μ_T	R^2	Sig.	Equation σ_T	R^2	Sig.
1	$(0.017 + 1.871\sqrt{N})(R)$	.998	<.0001*	$(0.990 - 0.064 \ln N)(R)$	.528	.0075*
2	$(1.862 + 1.744\sqrt{N})(R)$	.999	<.0001*	$(1.591 - 0.199 \ln N)(R)$	.832	.0308*
3	$(2.776 + 1.770\sqrt{N})(R)$	.999	<.0001*	$(1.864 - 0.245 \ln N)(R)$	.871	.0206*
4	$(3.721 + 1.706\sqrt{N})(R)$	.998	<.0001*	$(2.336 - 0.367 \ln N)(R)$	.861	.0229*
5	$(4.666 + 1.794\sqrt{N})(R)$	.989	.0005*	$(2.789 - 0.434 \ln N)(R)$	.940	.0063*

LAST MILE DELIVERY FLEET PLANNING MODEL FORMULATION

Using the stochastic last mile delivery framework, a last mile delivery fleet planning model is formulated to determine the optimal number of vehicles and the optimal number of days to deliver per week subject to the demand distribution, costs associated with the deliveries, the number of hours available per day to make deliveries, radius of the demand region, average vehicle speed in the region, average time spent per delivery stop, and vehicle payload capacity.

The following assumptions are adopted. Distance is measured in miles using the Manhattan (L_1) distance metric. A fleet of vehicles is available for use from a central depot. In this example, the vehicles are contracted so the model does not specify the acquisition cost of each vehicle, but this could be explored over a long-term planning horizon if appropriate for the company. The company in this scenario has some flexibility in its weekly delivery plan. For example, a home improvement store could choose to deliver just three days per week with one vehicle if demand was low, or it could be delivering seven days per week with five vehicles if demand was high.

Notation where T and D are the decision variables is as follows.

C_E = CO_2 emission cost per gallon of fuel
C_F = fuel cost ($/gallon of fuel)
C_M = maintenance cost ($/mile)
C_W = labor wage rate per hour
D = number of delivery days per week
H = feasible delivery hours per day
H_W = regular time labor hours available per week
P = wage premium for overtime (percent above regular wage rate)
N = the number of nodes including the depot.
$n = N - 1$; the number of customers or delivery points.
R = the radius (in miles) of the circular demand region
V = average speed of delivery vehicles in miles per hour
T = number of delivery vehicles
A = average time spent at each stop or customer location in hours
$TC(T, D)$ = total cost as a function of T and D
$m^* = TV[H_W - DA(N-1)]$; regular time delivery miles available per week
$m_D^* = TV[H - A(N-1)]$; total feasible delivery miles per day
L = beginning vehicle payload (lbs)
β_0 = miles per gallon (MPG) of an empty vehicle
β_1 = loss of MPG for each lb of payload ($\beta_1 < 0$)
β_A = fuel used while idling (gallons per hour)
A_B = percent of time vehicle is left running at delivery stops ($0 \le A_B \le 1$)
S = successful delivery rate ($0 \le S \le 1$)
C_T = traffic congestion factor ($0 \le C_T \le 1$)
E_F = amount of CO_2 emitted per gallon of fuel

μ_{L_W} = mean customer order weight in lbs.
σ_{L_W} = standard deviation of customer order weight in lbs.
μ_{L_V} = mean customer order volume in ft^3
σ_{L_v} = standard deviation of customer order volume in ft^3
L_W^* = weight capacity of a vehicle in lbs.
L_V^* = volume capacity of a vehicle in ft^3

Let $f(m)$ denote the weekly distribution of miles $\sim N\left(D\mu_T, \sqrt{D\sigma_T^2}\right)$, which is dependent on N, R, and T.

Let $\Phi^{-1}(\cdot)$ represent the inverse Gaussian giving the miles associated with the cumulative probability contained within the parentheses.

Let $f(N)$ denote the demand function. The number of delivery cycles determines how the weekly demand distribution breaks down for each cycle. For example, if the weekly demand distribution is normally distributed and $D = 3$, then $f(N)$ equals the weekly demand mean divided by 3 and the expected daily demand has standard deviation equal to the square root of the weekly demand variance after being divided by 3. Thus, if the weekly demand mean is 100 customers and $D = 4$, then an average of 25 customers would be visited on each of the four delivery days. If D were changed to 5, then an average of 20 customers would be visited on each of the five delivery days.

Let $p = 1 - \frac{\int_{m^*}^{\infty} f(m)dm}{2}$; the cumulative probability of the calculated midpoint, which is the point that bisects the probability of being greater than m^*.

Let $f(L_W)$ denote the distribution of the payload weight of individual customer orders $\sim N\left(n\mu_{L_W}, \sqrt{n\sigma_{L_W}^2}\right)$.

Let $f(L_V)$ denote the distribution of the payload volume of individual customer orders $\sim N\left(n\mu_{L_V}, \sqrt{n\sigma_{L_V}^2}\right)$.

Last Mile Delivery Fleet Planning Model Definition

The total weekly cost of meeting customer demand, $TC(T,D)$, is defined as the sum of maintenance cost, regular labor cost, overtime labor cost, fuel cost, and carbon emissions cost. This total cost function is as follows.

$$
\begin{aligned}
TC(T,D) = {} & C_M D \int_{N=1}^{\infty} \mu_T f(N)dN + C_W D \int_{N=1}^{\infty} \left(\frac{\mu_T}{V} + A(N-1)\right) f(N)dN \\
& + C_W P \left[AD \int_{N=1}^{\infty} \left(\frac{(\Phi^{-1}(p) - m^*)\left(\int_{m^*}^{\infty} f(m)dm\right)}{\frac{\Phi^{-1}(p)}{N-1}} \right) f(N)dN \right. \\
& \left. + \int_{N=1}^{\infty} \left(\frac{(\Phi^{-1}(p) - m^*)\left(\int_{m^*}^{\infty} f(m)dm\right)}{V} \right) f(N)dN \right] \\
& + (C_F + C_E) D \left(\frac{\int_{N=1}^{\infty} \mu_T f(N)dN}{\beta_0 + \beta_1 L\left(1 - \frac{S}{2}\right) C_T} + A_B \beta_A \int_{N=1}^{\infty} (A(N-1)) f(N)dN \right)
\end{aligned}
\tag{1}
$$

When examining the total cost equation (1), note that for a given radius of the demand region, R, the expected distance traveled per day, μ_T, is a function of the number of vehicles, T, and the node size, N. The total cost equation defined in (1) represents the summation of five different costs: maintenance, regular labor, overtime labor, fuel, and carbon emissions.

Total maintenance cost in (1) is defined by multiplying maintenance cost per mile, C_M, by expected distance traveled. The expected distance traveled is based on the number of delivery days,

D, multiplied by the distribution of expected demand, which depends on the number of delivery vehicles employed.

The total labor cost in (1) is defined by a summation of regular labor costs and overtime costs. In the first part, the labor wage, C_W, is multiplied by the number of delivery days, D, and then by the total labor hours expected per day. Calculating the total labor hours per day is based on the distribution of expected demand where the travel distance, μ_T, is divided by the average vehicle speed, V, and then time spent at delivery stops, $A(N-1)$, is added in.

The second part of calculating total labor costs involves an overtime cost, which applies if the weekly hours per vehicle exceed the regular wage time available. Overtime is composed of any time above the regular wage labor hours available per week spent at delivery stops and driving. The overtime cost associated with delivery stop time is estimated by finding the probability of exceeding m^* for the week and then using the midpoint method (see Figure 1) to find the point at which that area is halved. That midpoint can be thought of as the expected total distance traveled when m^* is exceeded. The midpoint is then used to calculate the average distance between nodes by dividing the midpoint by the number of nodes. The difference between the midpoint and the expected total weekly distance, $D\mu_T$, is then divided by this average distance between nodes to determine the approximate number of expected missed deliveries when m^* is exceeded. Next, multiplying this value of the expected number of delivery stops that occur when m^* is exceeded by the probability that m^* is exceeded gives the overall number of expected overtime delivery stops. Finally, multiplying this overall number of expected overtime delivery stops by the average time spent at each stop gives the number of expected overtime hours spent at delivery stops per week.

The time spent driving is found similarly, but the difference between the midpoint and the total weekly distance, $D\mu_T$, is multiplied by the probability of exceeding m^* and then divided by the average speed, V, to find the expected hours of overtime spent driving per week. These expected overtime hours are then multiplied by the labor wage premium since the regular wage rate has already been applied.

Figure 1: The Midpoint Used in the Calculation of Overtime

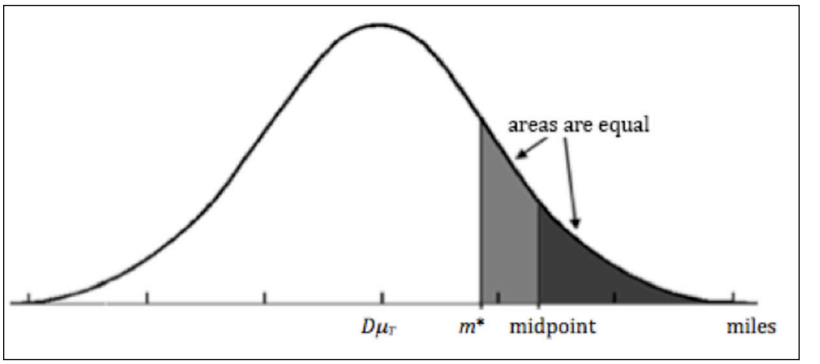
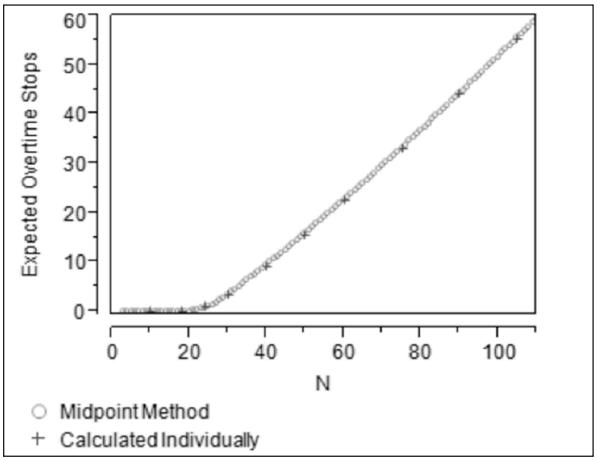


Figure 2 compares one parameterized example of the midpoint method of determining the expected number of overtime delivery stops with the computationally arduous method of calculating them for each level of demand individually. Since each number of customers has its own probability of occurring and within each of those, there is a probability associated with how often each would require overtime as well as the degree of overtime required, and calculating each individually is extensive. The midpoint method developed here is more computationally efficient and produces similar results.

Figure 2: Example of Overtime Delivery Stops Calculations



The final component of (1) includes both the fuel cost and carbon emissions cost. According to Ülkü (2012), the carbon emissions cost is "a cost figure that is calibrated by management." Zhang et al. (2015) model these costs similarly, allowing a decision maker to set these parameters as desired. See Chaabane et al. (2012) for an example of how a cost can be applied to total carbon emissions. Both fuel and carbon emission costs are based on the total gallons of fuel used and can be affected by average miles per hour, payload, time spent idling at delivery stops, and traffic congestion (Ülkü 2012). In equation (1), fuel cost, C_F, and carbon emissions cost, C_E, are multiplied by delivery days, D, and then by the expected gallons of fuel used per day, which includes both driving and idling at delivery stops. The expected gallons of fuel used while driving is determined by total mileage traveled per day divided by average fuel efficiency. Since fuel efficiency is affected by traffic congestion and payload weight, these factors and missed deliveries are taken into consideration to compute average fuel efficiency (Suzuki 2011; Xiao et al. 2012). Finally, fuel used while idling at delivery stops is calculated based on the likelihood of idling at a delivery stop multiplied by the gallons of fuel used per hour idling and then multiplied by the average time spent at delivery stops per day, which depends on the demand distribution.

Separating the calculation of total gallons of fuel used from (1), the total amount of weekly CO_2 emissions, $E(T, D)$, shown in (2), is defined as the amount of CO_2 emitted per gallon of fuel, E_F, multiplied by gallons of fuel used.

$$(2)\quad E(T,D) = E_F D\left(\frac{\int_{N=1}^{\infty}\mu_T f(N)dN}{\beta_0 + \beta_1 L\left(1-\frac{S}{2}\right)C_T} + A_B\beta_A\int_{N=1}^{\infty}\big(A(N-1)\big)f(N)dN\right)$$

From a managerial perspective, service level is another important consideration that must be addressed in addition to total cost when comparing alternative delivery options. For instance, if normal delivery hours were 8:00 AM to 6:00 PM, then delivering at 9:00 PM would not be desirable. This model allows a general delivery window to be set and will record the associated on-time delivery service levels. The on-time delivery service level, which is defined as the percentage of time that deliveries are made within the daily delivery window, is shown in (3).

$$(3)\quad \int_0^{m_D^*} f(m)dm$$

Payload weight and volume are captured as random variables and a service level is found for each delivery scenario. Similar to the on-time service level, a manager will choose relevant service levels for payload weight and volume in order to assure that the payload capacity of the vehicle is not exceeded. Service levels for daily payload weight and volume are defined in (4) and (5), respectively.

(4) $\int_0^{L_W^*} f(L_W)dL_W$

(5) $\int_0^{L_V^*} f(L_V)dL_V$

Model Illustration with a Numerical Example

In this section, the model is illustrated under a what-if scenario where the demand function is altered to simulate an expected spike in future customer demand. In this example, the company owns five delivery vehicles, which can adequately cover demand during peak times. However, demand is variable throughout the year. The following parameter values, modeled for a furniture store, have been assigned to support the model illustration:

C_E = \$0.02; C_F = \$3.80; C_M =\$0.05; C_W = \$20; H = 12; H_W = 40; P = 0.5; R = 25; V = 30; A = 0.05; β_0 = 10; β_1 = -0.0005; β_A = 0.5; A_B = 50%; S = 90%; C_T = 1; E_F = 10.18 kilos; μ_{L_W}= 80; σ_{L_W}= 15; μ_{L_V}= 10; σ_{L_v}= 2; L_W^* = 4000; L_V^* = 500; $f(N)$ is derived from weekly demand ~ N(300, 20).

The model was solved in an Excel spreadsheet. Probabilities from the demand distribution were applied to discrete values for the number of possible customers. Table 2 shows the results after removing any combinations of vehicles and delivery days resulting in service levels below 90% for available delivery hours and 95% for payload capacity (weight and volume). Based on the results, some managerial insight is needed to make the final delivery scenario decision based on the manager's preference toward desired service levels. Thus, an absolute optimization is undesirable since providing multiple feasible options allows more insight and the flexibility to make informed decisions that meet customer needs and company objectives. In this example, the manager would likely conclude that using four vehicles delivering three days per week is the best possible option in terms of cost and acceptable service levels. The combinations of vehicles and delivery days with a service level below 95% have been italicized.

Table 2: Results for Alternative Delivery Scenarios

Vehicles	Days	Operating Cost	On-Time Service Level	Payload Weight Service Level	Payload Volume Service Level	CO_2 emissions (kilos)
2	*4*	*$2,387*	*90.2514%*	*99.4093%*	*99.3914%*	*2101*
	5	$2,696	99.8671%	99.9995%	99.9994%	2284
	6	$2,987	99.9994%	100.0000%	100.0000%	2464
	7	$3,262	100.0000%	100.0000%	100.0000%	2639
3	*3*	*$2,161*	*94.1135%*	*99.9986%*	*99.9984%*	*2039*
	4	$2,434	99.9987%	100.0000%	100.0000%	2240
	5	$2,708	100.0000%	100.0000%	100.0000%	2447
	6	$2,992	100.0000%	100.0000%	100.0000%	2652
	7	$3,280	100.0000%	100.0000%	100.0000%	2851
4	**3**	**$2,189**	**99.9764%**	**100.0000%**	**100.0000%**	**2069**
	4	$2,477	100.0000%	100.0000%	100.0000%	2287
	5	$2,752	100.0000%	100.0000%	100.0000%	2513
	6	$3,018	100.0000%	100.0000%	100.0000%	2736
	7	$3,283	100.0000%	100.0000%	100.0000%	2955
5	3	$2,354	99.9995%	100.0000%	100.0000%	2247
	4	$2,678	100.0000%	100.0000%	100.0000%	2495
	5	$2,987	100.0000%	100.0000%	100.0000%	2751
	6	$3,283	100.0000%	100.0000%	100.0000%	3005
	7	$3,571	100.0000%	100.0000%	100.0000%	3253

The responsiveness of the model to handling changes in customer demand is demonstrated by increasing weekly demand from ~N(300, 20) to ~N(360, 25) to simulate an increase in demand. Table 3 compares the results from each feasible scenario in Table 2 with this increase in demand. The combinations of vehicles and delivery days with a service level below 95% have been italicized to indicate that these options would likely be considered undesirable. As illustrated in Table 3, the former best choice of four vehicles delivering three days per week returns an on-time service level of just 92.56%. Therefore, the manager would need to change the delivery plan to avoid an unacceptable decrease in the service level resulting from the increase in demand. The best choice appears to be either a fleet of five vehicles delivering the same three days per week or the same fleet of four vehicles, but now delivering four days per week. The ultimate decision between the two delivery policies would come down to preferences among cost, delivery plan, and comfort level with the service levels since the four vehicles delivering four days per week is slightly more expensive and higher polluting, but offers a higher service level.

Table 3: Results for Alternative Delivery Scenarios

Vehicles	Days	Operating Cost	On-Time Service Level	Payload Weight Service Level	Payload Volume Service Level	CO2 emissions (kilos)
2	*4*	*$2,786*	*45.8416%*	*80.6083%*	*80.5481%*	*2378*
	5	*$3,117*	*92.3368%*	*99.4259%*	*99.4117%*	*2558*
	6	$3,427	99.6214%	99.9951%	99.9947%	2741
	7	$3,718	99.9900%	100.0000%	100.0000%	2920
3	*3*	*$2,425*	*45.9895%*	*98.0993%*	*98.0553%*	*2336*
	4	$2,753	98.7236%	99.9998%	99.9998%	2525
	5	$3,092	99.9975%	100.0000%	100.0000%	2729
	6	$3,427	100.0000%	100.0000%	100.0000%	2936
	7	$3,751	100.0000%	100.0000%	100.0000%	3141
4	*3*	*$2,441*	*92.5563%*	*99.7496%*	*99.7496%*	*2361*
	4	**$2,747**	**99.9972%**	**100.0000%**	**100.0000%**	**2568**
	5	$3,050	100.0000%	100.0000%	100.0000%	2790
	6	$3,363	100.0000%	100.0000%	100.0000%	3015
	7	$3,681	100.0000%	100.0000%	100.0000%	3238
5	**3**	**$2,617**	**98.5539%**	**99.7496%**	**99.7496%**	**2558**
	4	$2,956	100.0000%	100.0000%	100.0000%	2793
	5	$3,282	100.0000%	100.0000%	100.0000%	3045
	6	$3,609	100.0000%	100.0000%	100.0000%	3301
	7	$3,942	100.0000%	100.0000%	100.0000%	3554

The methodology demonstrated presents a decision framework that managers could use for assessing the size and delivery plan of the vehicle fleet needed to satisfy customer demand in the context of a stochastic representation of the LMP. Clearly, the results demonstrated are parameter specific. Therefore, a sensitivity analysis was performed on the key parameters to better understand the features of the model.

Parameters associated with emissions, maintenance, and fuel costs (C_E, C_M, and C_F) were analyzed across a range with upper and lower bounds just outside of realistic values and did not change the resulting policy decision when changing individually or simultaneously. For the sensitivity analyses conducted, only the magnitude of the dollar difference between the solutions changed with all policy decisions remaining unchanged. Large changes to the labor wage rate per hour, C_W, however, did have an impact on the rank order of the solution set because of the effect on overtime cost.

Any parameters that impact expected overtime or service levels in some way will have an impact on the solution set. So changing A, R, V, H, and H_W can all alter the feasibility of making the necessary deliveries in the allotted amount of time and, thus, affect the feasible solutions and the rank order of the solution set. Changes in these parameters within the feasibility range will only impact total cost and the solution set as they begin to incur overtime costs and then will ultimately be kicked out as the delivery option's service level falls out of the acceptable range.

In addition, all parameters associated with the demand function, customer order weight and volume functions, and vehicle payload capacity (weight and volume) can strongly affect the service levels and, therefore, the feasible solutions and rank order of the solution set.

While the total cost function was found to not be convex, the sensitivity analysis shows that the parameters most responsible for impacting the optimal solution are those that affect the feasibility of making the required deliveries within the allotted time available for delivery. As these parameters change and constrict the feasibility and probability of successfully making the necessary deliveries,

certain delivery combinations become infeasible. The model provides decision makers with the ability to compare delivery alternatives in order to choose the delivery option with the best mix of cost, carbon emissions, and service level. Another contribution of this model is the model's ability to highlight the differences in carbon emissions among decision alternatives that are similar in total cost and service level.

CONCLUSIONS

The last mile delivery fleet planning model presented herein defines a mathematical model that, for a given set of parameters, can be used to determine a decision maker's preference in the combination of the number of vehicles and delivery days per week for delivering to end customers in a supply chain while taking on-time delivery and payload service levels into consideration. The framework presented extends distance-based models found in the literature by adopting a modeling structure that uniquely addresses the set of customer demand points found in the delivery region while also incorporating the cost of CO_2 emission into the model formulation. The model uniquely addresses the forward-looking nature of planning with uncertainty and adds to the literature by allowing a manager to perform what-if analyses to explore potential changes in delivery policy decisions based on cost, carbon emissions, and service levels by modifying inputs, such as the demand distribution, payload distributions, traffic congestion, fuel efficiency, time spent idling at delivery stops, and vehicle capacity.

A major contribution of the last mile delivery fleet planning model presented in this paper is incorporating stochastic demand into the LMP in a varying multiple vehicle delivery environment, incorporating carbon emissions that result from vehicle transportation into the LMP, and the development of a planning model that incorporates uncertainty in terms of expected mileage and labor hours. The last mile delivery fleet planning model advances the literature by creating a decision framework that includes a distribution of expected travel distance, probabilistic service levels, a carbon emissions component, and a multiple vehicle fleet of varying size. The combination of these factors in one delivery fleet planning model improves the quality of information available to plan properly, enhances overall decision-making, and adds to the literature with the ability to gauge the probabilistic likelihood of service levels and costs associated with solving the LMP. Managers can use the output from this model to explore fleet combinations as demand changes from week to week with more information than was previously available.

There are several aspects of the stochastic last mile delivery framework and the last mile delivery fleet planning model that can be extended. First, the model could be adapted such that carbon emission is constrained subject to a carbon trading/credit scheme. Second, the model could be expanded to include multiple depots within each region or sub region. Last, additional components including, but not limited to, vehicle purchase, depreciation cost, loading costs, labor burden, and/or driver salaries could be added to the model.

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

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