

USDOT Region V Regional University Transportation Center Final Report

NEXTRANS Project No. 0910Y04

# IMPACT OF PUBLIC TRANSPORTATION MARKET SHARE AND OTHER TRANSPORTATION AND ENVIRONMENTAL POLICY VARIABLES ON SUSTAINABLE TRANSPORTATION

By

Rabi G. Mishalani, Principal Investigator Associate Professor of Civil and Environmental Engineering and Geodetic Science The Ohio State University mishalani@osu.edu

and

Prem Goel, Co-Principal Investigator Professor of Statistics The Ohio State University goel.1@osu.edu



#### DISCLAIMER

Funding for this research was provided by the NEXTRANS Center, Purdue University under Grant No. DTRT07-G-005 of the U.S. Department of Transportation, Research and Innovative Technology Administration (RITA), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.



USDOT Region V Regional University Transportation Center Final Report

## **TECHNICAL SUMMARY**

NEXTRANS Project No. 0630Y03

Final Report, Jan. 21, 2015

## Impact of Public Transportation Market Share and other Transportation and Environmental Policy Variables on Sustainable Transportation

## Introduction

Policies that encourage reduced travel, such as traveling shorter distances, and increased use of more efficient transportation modes, such as public transportation and high-occupancy private automobiles, are often considered one of several possible tools aimed at improving the sustainability of transportation. This study develops a statistical model that provides an important step towards quantifying the possible benefits that could be derived from such policies in terms of potential reductions in greenhouse gas (GHG) emissions.

The contributions of this study are fourfold. First, an aggregate model of urban passenger travel related CO2 emissions in US urbanized areas that includes a rich set of explanatory variables is developed. Second, in doing so, the roles of policies aimed at improving the environment or could enhance the attitudes of travelers towards making environmentally favorable choices is captured through the use of a proxy variable. Third, the possible presence of selectivity bias resulting from the hypothesized effects of such environment enhancing policies is accounted for in the model estimation. Fourth, as a result, an improved quantification of the explanatory effects of transportation demand and supply, population density, and policy variables is arrived at.

#### **Findings**

The statistically significant differences in the estimated coefficients across the auto inspection and no inspection model segments provide evidence for the important role the inspection variable plays as a proxy of the presence of environmental policies and environmentally favorable travel behaviors and attitudes. Specifically, the estimation results indicate that the possible presence of environmentally favorable policies or behaviors significantly alters the roles transportation demand and supply variables play in explaining  $CO_2$  emissions.

For example, in the absence of environmentally favorable policies or travelers' attitudes and behaviors, the contributions of increased transit share, reduced average travel time, and increased average vehicle occupancy towards reducing CO<sub>2</sub> emissions per capita are larger than the corresponding contributions in the presence of environmentally favorable policies or travelers' attitudes and behaviors. Moreover, in the possible presence of environmentally favorable travelers' attitudes and behaviors stemming from

the awareness that could be brought about from automobile inspection programs, reducing freeway miles per capita yields higher reductions in CO<sub>2</sub> emissions than the corresponding reductions in the absence of such attitudes and behaviors. Similarly, in the possible presence of environmentally favorable travelers' attitudes and behaviors associated with the presence of automobile inspection programs, increasing population density yields reductions in CO<sub>2</sub> emissions, while in the absence of such attitudes and behaviors associated statistically significant role.

#### **Recommendations**

It would be worthwhile to use the estimated segmented model where selectively bias is corrected for to quantify the impacts of hypothetical changes in the various variables on  $CO_2$  emissions for select urbanized areas spanning the range of  $CO_2$  emissions per capita, population sizes, and falling in the two automobile inspection program categories. In addition, it is important to identify the policy implications of the quantified impacts. Specifically, in would be valuable to identify the variables that have the most impact on changing  $CO_2$  emissions, explore the comparative impacts of the various variables, and probe the value and limitations of the developed model for the purpose of policy-making. More broadly, the role and use of such a model in understanding the interactions between policy and travel behavior and, consequently, in policy-making clearly warrant further investigations.

#### **Contacts**

#### For more information:

#### Rabi G. Mishalani

Principal Investigator Associate Professor of Civil, Environmental and Geodetic Engineering The Ohio State University mishalani@osu.edu

**Prem Goel** Co-Principal Investigator Professor of Statistics The Ohio State University goel.1@osu.edu NEXTRANS Center Purdue University - Discovery Park 3000 Ken Ave West Lafayette, IN 47906

nextrans@purdue.edu

(765) 496-9729 (765) 807-3123 Fax

www.purdue.edu/dp/nextrans

#### ACKNOWLEDGMENTS AND DISCLAIMER

Partial funding for this research was provided by the NEXTRANS Center, Purdue University under Grant No. DTRT07-G-005 of the U.S. Department of Transportation, Research and Innovative Technology Administration (RITA), University Transportation Centers Program. Additional funding was provided by The Ohio State University (OSU) including the College of Engineering and the Department of Statistics.

The efforts of Graduate Research Assistants Andrew Landgraf and Ashley Westra are greatly appreciated.

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

## **TABLE OF CONTENTS**

1. INTRODUCTION AND MOTIVATION	4
2. MODEL DEVELOPMENT	4
2.1 Data and Variables	4
2.2 Preliminary Model	5
2.3 Segmented Model	5
2.4 Result Interpretations	8
3. NEXT STEPS	10
4. REFERENCES	11
LIST OF TABLES	
TABLE 1: Estimation results of the binary logit model for the decision to adopt an	
inspection program	7
TABLE 2: Estimation results of segmented regression model for CO <sub>2</sub> per capita	8

### **1. INTRODUCTION AND MOTIVATION**

Policies that encourage reduced travel, such as traveling shorter distances, and increased use of more efficient transportation modes, such as public transportation and high-occupancy private automobiles, are often considered one of several possible tools aimed at improving the sustainability of transportation. This study develops a statistical model that provides an important step towards quantifying the possible benefits that could be derived from such policies in terms of potential reductions in greenhouse gas (GHG) emissions.

In general, passenger transportation related energy consumption and GHG emissions per capita in urbanized areas are expected to be dependent on the supply and demand characteristics of the multiple modes of passenger travel in these areas. Naturally, an overall reduction in travel leads to lower GHG emissions. Moreover, due to the efficient nature of public transportation and the greater flexibility this mode offers in using different sources of energy, it is expected that, in general, an increase in the use of transit services could lead to a reduction in GHG emissions. Similarly, higher private vehicle occupancy is expected to mitigate the negative impacts of the single-occupancy vehicle mode, again in the form of reduced GHG emissions. Furthermore, population density has the potential to contribute to reduced travel and the adoption of policies and services that encourage more efficient modes. In addition to understanding the explanatory effects of transportation mode choice, the supply of transportation services, and population density, it is equally important to take into account the direct or indirect effects of government policies aimed at reducing GHG emissions.

In this study, only  $CO_2$  emissions are examined since these emissions constitute 93.4% of the GHG produced in the transportation sector (Energy Information Administration, 2008). In addition, the  $CO_2$  emissions focused on are those resulting from passenger travel and the roles of travelers' choices within the confines of available infrastructure and existing urban form. Therefore, unlike other studies, freight transportation is not considered. Moreover,  $CO_2$ emissions resulting from the construction of transportation infrastructure and the manufacturing of passenger vehicles (private and public) are outside the scope of this study.

The contributions of this study are fourfold. First, an aggregate model of urban passenger travel related  $CO_2$  emissions in US urbanized areas that includes a rich set of explanatory variables is developed. Second, in doing so, the roles of policies aimed at improving the environment or could enhance the attitudes of travelers towards making environmentally favorable choices is captured through the use of a proxy variable. Third, the possible presence of selectivity bias resulting from the hypothesized effects of such environment enhancing policies is accounted for in the model estimation. Fourth, as a result, an improved quantification of the explanatory effects of transportation demand and supply, population density, and policy variables is arrived at.

#### 2. MODEL DEVELOPMENT

#### 2.1 Data and Variables

The response variable of interest is the annual metric tons of  $CO_2$  per capita emitted in an urbanized area in the US as a direct result of passenger transportation using all modes of travel. The explanatory variables considered in this study are transit share, transit service utilization,

#### R.G. Mishalani & P.K. Goel

average vehicle occupancy, lane miles per capita, average travel time, population density, degree of variation in population density, and the presence or absence of an automobile emissions inspection program. The involved process of determining the values of these variables and creating an integrated cross-sectional dataset from multiple sources for the largest 146 urbanized areas in the US for the years 2000-2003 is described in Mishalani and Goel (2011). The explanatory variables are described in detail in Mishalani and Goel (2015).

Notable among the considered variables, is the binary indicator of whether urbanized areas have regulations in place that require that vehicles are inspected for emissions on a regular basis (usually annually) and are maintained if emissions levels exceed specified thresholds. While these inspection programs are federally mandated to address emissions of pollutants such as hydrocarbons (HC), carbon monoxide (CO), oxides of nitrogen (NOx), and volatile organic compounds (VOCs) – and not GHG emissions (Rilett, 2002), the presence of such inspections in an urbanized area could be viewed as a proxy indicator of the presence of other policies and regulations aimed at mitigating environmental concerns, some of which could be related to GHG emissions. While the Clean Air Act amendments of 1990 mandated all cities that do not meet federal health standards to implement emission inspection programs, the majority of the cities (70 of 110) that were required to implement the inspections in 1990 already had such programs in place, indicating that the policy-makers of many of these cities were conscious of and acted proactively to curb the effects of pollution prior to the 1990 mandate (Almanac of Policy Issues, 2002). Such policy actions may have already been extended to address GHG emissions as well. The presence of inspection programs may influence policy-makers by highlighting the environmental costs of transportation leading to their adopting a more aggressive stand in relation to environmental issues in general, including GHG emissions.

To illustrate the proxy nature of the inspection variable in terms of its ability to indicate the presence of other policies or regulations that have an effect on GHG emissions, consider the specific case where certain states adopted the California Air Resources Board (CARB) standards, which include improved fuel efficiency aimed specifically at reducing GHG emissions. While none of these GHG standards were in effect in 2000 (DieselNet, 2011), the year corresponding to the automobile inspection proxy variable in the dataset used, it is worthwhile to explore the degree of association between the presence of automobile inspection programs in 2000 and the adoption of CARB standards by 2011 (Center for Climate and Energy Solutions, 2011). Of the 70 cities that had inspection programs in 2000, the states of 41 (59%) adopted CARB standards by 2011. Of the 76 that did not have inspection, only 8 (11%) adopted these standards. The Chi-squared test for independence of these two variables has a p-value of 2.425 10-9, indicating that there is a very strong association between the two variables.

In addition to inspection providing a possible indication of other policies and regulations, it could also have a favorable effect on the attitudes of travelers by raising awareness, possibly causing them to make better choices regarding the miles per gallon (MPG) levels of vehicles they purchase, drive in a manner that produces less  $CO_2$  emissions, or select more efficient travel modes such as public transportation and high occupancy private automobiles. Gaker et al. (2011) found that people are willing to change their travel behavior to reduce  $CO_2$  emissions, even if doing so comes with a higher personal cost in terms of time or money. Jariyasunant et al. (2014) found experimental subjects significantly reducing driving in response to feedback they received on the environmental footprint of their prior travel choices.

## 2.2 Preliminary Model

An initial model is developed and presented in Mishalani and Goel (2015) where it was determined that the explanatory variables that contribute to  $CO_2$  per capita levels in a statistically significant manner are transit share, lane miles per capita, average travel time, average vehicle occupancy, and 1/density. Since it is believed that the implementation of an emissions inspection program can be viewed as a proxy for the presence of other policies and regulations aimed at mitigating GHG emissions and may encourage favorable travel choices that could lead to reduced GHG emissions, an indicator variable representing the presence of an automobile emissions inspection program in an urbanized area is also included in the preliminary model. This variable takes the value of one for urbanized areas with an emissions inspection program and zero otherwise. The estimated coefficients of all of the explanatory variables have the expected signs.

While the estimated coefficient of the indicator variable for emissions inspections does have a negative sign, suggesting that the presence of inspections is associated with lower  $CO_2$ per capita in an urbanized area, it is not found to be statistically significant. That is, the estimated preliminary model shows that simply adding a binary variable indicating whether or not an urbanized area has an emissions inspection program in place does not improve the model (the coefficient estimates and their statistical significance are similar to those of a model where the indicator variable is not included in the specification), even though this variable is hypothesized to have an explanatory effect on  $CO_2$  per capita.

## 2.3 Segmented Model

The insignificance of the estimated coefficient of the inspection indicator variable could be due to the possible presence of two relationships involving automobile emissions inspection programs and  $CO_2$  emissions that counter the effects of one another. While the presence of an inspection program in an urbanized area could be indicative of other policies and regulations that reduce GHG emissions, adopting an inspection program in an urbanized area aimed at reducing pollutants emissions levels and adopting other policies aimed at reducing GHG emissions in the same urbanized area are likely to be partly driven by the presence of environmental concerns in that area associated with higher levels of  $CO_2$  emissions. Therefore, a possible self-selection into an emissions inspection category may be at play among the urbanized areas in the dataset due to this simultaneity, thus, leading to a selectivity bias in the model's coefficients estimates discussed in section 2.2.

An approach presented in Mannering (1987) and Washington et al. (2003) is used in this study to investigate the presence of and correct for this possible selectivity bias. The methodology consists of determining selectivity bias correction variables that could be introduced into a segmented model specification consisting of one relationship for urbanized areas with inspection and one for those without inspection. Doing so corrects for the effect of self-selection on the estimated coefficients of the other explanatory variables. Calculating the selectivity bias correction variables requires the probabilities of an urbanized area adopting and not adopting an emissions inspection program and, thus, the estimation of a decision model relating an urbanized area's adoption of an automobile emissions inspection program to explanatory variables that drive such a decision.

#### R.G. Mishalani & P.K. Goel

To determine the probability of an urbanized area adopting an emissions inspection program, a binary logit model is developed with appropriate explanatory variables. Since, as discussed in Section 2.1 inspections are intended to control the levels of carbon monoxide (CO) and oxides of nitrogen (NOx) among other transportation related pollution emissions and not  $CO_2$  and other GHG emissions (hence, the proxy nature of the emissions inspection indicator variable), CO and NOx emission levels are reasonable explanatory variables to consider. The source of these variables used in this study is the 2002 National Emissions Inventory Data (NEID) (US EPA, 2012).

The CO and NOx pollution variables can be normalized by either the land area or the population of the urbanized area. The former (i.e., using CO per unit area and NOx per unit area as explanatory variables) resulted in a better model fit. The fit was first assessed by comparing the empirical cumulative distribution functions for the fitted probabilities of adopting emissions inspection for urbanized areas with and without such inspection programs by noting both their separation and how concentrated they are with respect to their true values of 1 and 0, respectively. Normalizing by area leads to a better fit on both accounts. Moreover, the goodness-of-fit of the two estimated decision models as measured by the difference between the deviance of the estimated model and the deviance of the model specified without any explanatory variables (which is given by  $-2[\mathcal{L}(c) - \mathcal{L}(\hat{\beta})]$  where  $\mathcal{L}(c)$  is the log-likelihood corresponding to the model in which the choice probabilities are equal to the fractions of urbanized areas in each inspection category and  $\mathcal{L}(\hat{\beta})$  is the maximum log-likelihood of the estimated model) shows that the decision to adopt an emissions inspection program is better explained by the pollution levels within an area. This result is reasonable given that the environmental and health impacts of pollution are due to emissions in an entire area, affecting everyone who lives in the area.

Table 1 shows the estimation results of the binary logit model where the utility of the decision not to adopt an automobile emissions inspect program is used as a reference. The signs of the coefficients of the two explanatory variables differ. It is expected that increasing pollution per unit area should be associated with an increase in the probability of that urbanized area having emissions inspections. Therefore, the positive sign for the coefficient of NOx/area is expected. The negative sign for the coefficient of CO/area is indicative of a strong interaction between the two variables. Indeed, their correlation coefficient is 0.992. However, including an interaction term between the two variables in the model does not lead to a statistically significant coefficient for this term, and removing the CO/area variable results in an inferior model in which the estimated coefficient of the remaining NOx/area variable is significant at a lower significance level. An analysis of deviance also shows that CO/area provides a significant improvement to the model with respect to the case where only NOx/area is included as an explanatory variable.

Explanatory variable	Coeff	Std err	z-stat	p-value			
Constant	- 0.262	0.343	- 0.765	0.444			
NO <sub>x</sub> /area	6.317	1.205	5.243	< 0.001			
CO/area	-0.440	0.083	- 5.285	< 0.001			
# of observations = 146; diff. in deviances = 77.1 (2 df); $\rho^2 = 0.3814$							

 TABLE 1: Estimation results of the binary logit model

 for the decision to adopt an inspection program

#### R.G. Mishalani & P.K. Goel

From this estimated binary logit model, the fitted probability of adopting an emissions inspection program for each of the 146 urbanized areas, based on their pollution emission levels, can be determined. Denote  $P_1$  to be the fitted probability that an urbanized area adopts an emissions inspection program. Naturally, the fitted probability that an urbanized area does not adopt an emissions inspection program is given by  $P_0 = 1 - P_1$ .

The selectivity bias correction (SBC) variables discussed previously are introduced as variables in the specification when estimating two separate linear in the parameters models, one using data of urbanized areas where inspection programs are present and the other where they are not, using ordinary least squares. The use of the SBC variables in the specifications is shown to result in coefficient estimates for all the explanatory variables that are corrected in a manner that eliminates the biases resulting from self selection (Mannering, 1987; Washington et al., 2003).

The SBC variables are defined as

. .

$$SBC_1 = \frac{P_0 \times \ln(P_0)}{2P_1} + \ln(P_1) \tag{1}$$

for urbanized areas with emissions inspection and as

$$SBC_0 = \frac{P_1 \times \ln(P_1)}{2P_0} + \ln(P_0)$$
<sup>(2)</sup>

for urbanized areas without emissions inspection. It can be shown that  $SBC_1$  is an increasing function with respect to  $P_1$  while  $SBC_0$  is a decreasing function with respect to  $P_1$ . Since CO<sub>2</sub> per capita is expected to be positively associated with CO/area and with NOx/area (as confirmed by the positive correlation coefficients among these pairs of variables), and since the probability that an urbanized area adopts an emissions inspection program  $P_1$  is also expected to be positively associated with CO/area and with NOx/area (again, as confirmed by the positive correlation coefficients among these pairs of variables),  $P_1$  is expected to increase with increasing CO<sub>2</sub>/capita. Therefore, the coefficient of  $SBC_1$  is expected to have a positive sign while the coefficient of  $SBC_0$  is expected to have a negative sign.

The urbanized areas are split into two separate groups by inspection category (70 urbanized areas with emissions inspection programs and another 76 without such programs), and separate regression models are estimated for each group using the corresponding SBC variables in addition to the explanatory variables. This segmentation allows the coefficients of all explanatory variables to be different based on whether emissions inspection programs are present or not. In contrast, in the preliminary model specification discussed in section 2.2 all of the coefficients are constrained to be equal for the two groups of urbanized areas. The estimation results of the segmented specification in the presence of the SBC variables where at least one of the two coefficient estimates of each explanatory variable is found to be statistically significant at a significance level of at least 0.10 are shown in Table 2. While the signs of the estimated coefficients of the selectivity bias correction variables *SBC*<sub>1</sub> and *SBC*<sub>0</sub> are consistent with the

expectations discussed above, the estimated value in the model for the urbanized areas without emissions inspection is found to be statistically significant and the estimated value in the model for urbanized areas with inspection is not found to be significant. An investigation of the empirical cumulative distribution functions of  $SBC_1$  and  $SBC_0$  shows that both the range and variance of  $SBC_1$  are smaller than those of  $SBC_0$ , providing an explanation of why this variable is not significant in the segmented model for urbanized areas with emissions inspection. The significance of one of the two SBC estimated coefficients, nevertheless, provides indication that self selection is likely present in the dataset.

	Inspection				No Inspection			
Explanatory variable	Coeff	Std err	t-stat	p-value	Coeff	Std err	t-stat	p-value
Constant	0.327	0.675	0.485	0.630	3.373	1.022	3.301	0.002
Transit Share	0.309	1.231	0.251	0.803	- 7.456	4.179	-1.784	0.079
Freeway Lane-mi/capita	1156.691	116.282	9.947	< 0.001	406.307	121.761	3.337	0.001
Average Travel Time	0.024	0.008	2.991	0.004	0.070	0.012	5.814	< 0.001
Avg. Priv. Veh. Occupancy	- 0.215	0.571	-0.376	0.708	- 3.054	0.920	-3.320	0.001
1/Density	393.198	190.696	2.062	0.043	- 25.158	289.587	-0.087	0.931
Selectivity Bias Correction	0.034	0.031	1.069	0.289	-0.081	0.037	-2.211	0.030
	# of observations = 70; $R^2 = 0.732$			# of ob	servations =	$= 76; R^2 = 0$	).519	

## 2.4 Result Interpretations

The p-values of the estimated coefficients of the explanatory variables indicate that transit share, freeway lane-miles per capita, average private vehicle occupancy, average travel time, and population density have statistically significant explanatory effects on  $CO_2$  emissions (with p-values associated with each of these variables being less than or equal to 0.079 at least in one of the two model segments). Moreover, and in contrast to the preliminary model estimation results where the coefficient of the inspection indicator variable is not found to be significant as discussed in Section 2.2, the presence of emissions inspection programs in urbanized areas appears to appreciably change the values of the estimated coefficients of most other variables.

Specifically, the significance of the differences between the estimated coefficients for each explanatory variable for urbanized areas with inspection and those without inspection is tested for. The two models for the two groups of urbanized areas were merged into a combined model by including, in addition to the existing set of explanatory variables, the product of the indicator variable representing the presence or absence of emissions inspection programs with each explanatory variable (recall, this indicator variable takes the value one in the presence of an emissions inspection program and zero otherwise). The selectivity bias correction variables are also included in this combined model specification in the form of an integrated selectivity bias correction variable that takes the value of  $SBC_1$  in the presence of inspection and  $SBC_0$  otherwise where  $SBC_1$  and  $SBC_0$  are as defined in Equations (1) and (2), respectively, and an additional interaction term consisting of the product of this integrated selectivity bias correction variable and the inspection indicator variable. Therefore, the coefficient of the product of the indicator variable with an explanatory variable in this combined model represents the difference between the coefficient of an explanatory variable in the presence of inspection and that of the same explanatory variable in the absence of inspection as reported in Table 2. Thus, testing if each of these coefficients is significantly different from zero is equivalent to testing if the two coefficients are significantly different from one another. Using this methodology, the coefficients for each explanatory variable, except 1/density, are found to be significantly different (with p-values less than or equal to 0.053).

The statistically significant differences in the estimated coefficients across the inspection and no inspection model segments provide evidence for the important role the inspection variable plays. Recall that, as discussed and illustrated in Section 2.1, the inspection variable could be considered a proxy indictor of policies urbanized areas might have in place that are aimed at reducing GHG emissions. In addition and as also discussed in Section 2.1, the inspection variable could be indicative of possible favorable travel choices travelers make as a result of the awareness brought about by emissions inspection programs. Consequently, the estimation results indicate that the possible presence of such policies or behaviors significantly alters the roles transportation demand and supply variables play in explaining CO<sub>2</sub> emissions. While the estimated coefficients of the 1/density variable for urbanized areas with and without inspection programs are not found to be statistically different from one another, the estimated coefficient in the presence of inspection programs is not found to be significantly different from zero (a statistically possible result given that the standard error of the difference between the coefficients could be larger than the standard errors of either coefficient).

More specifically, in the absence of environmentally favorable policies or travelers' attitudes and behaviors, the contributions of increased transit share, reduced average travel time, and increased average vehicle occupancy towards reducing  $CO_2$  emissions per capita are larger than the corresponding contributions in the presence of environmentally favorable policies or travelers' attitudes and behaviors (recognizing that in the presence of inspection the estimated coefficients of transit share and average vehicle occupancy are found not to be statistically significant). Such differences are not surprising as in the absence of such policies or attitudes and behaviors, more opportunities for reducing  $CO_2$  emissions through changes in these variables are expected.

Moreover, in the possible presence of environmentally favorable travelers' attitudes and behaviors stemming from the awareness that could be brought about from automobile inspection programs, reducing freeway miles per capita yields higher reductions in  $CO_2$  emissions than the corresponding reductions in the absence of such attitudes and behaviors. This difference could be explained as follows. The disincentive of private automobile travel brought about by reduced capacity for private automobile use in the form of reduced freeway-miles per capita likely leading to increased congestion could have a larger impact on shifts to more efficient forms of transportation by travelers who are more aware of the environmental concerns associated with transportation and, thus, are prone to be more sensitive to auto use disincentives in favor of more environmentally favorable travel choices.

Similarly, in the possible presence of environmentally favorable travelers' attitudes and behaviors associated with the presence of automobile inspection programs, increasing population density yields reductions in  $CO_2$  emissions, while in the absence of such attitudes and behaviors, this variable does not play a statistically significant role. This difference could be explained as follows. Incentives for reducing travel brought about by increased density could have a marked impact on shifts to more efficient forms of transportation by travelers who are more aware of the

environmental concerns and, thus, are prone to be more sensitive to incentives encouraging environmentally favorable travel choices brought about by higher densities, which by nature offer opportunities for more efficient travel.

Naturally, additional effects to the ones discussed could be taking place simultaneously and, thus, the estimation results only reveal the net explanatory effects of the freeway miles per capita and population density variables. Therefore, further investigations of the possible multiple effects these two variables might have are desirable as part of future research. Equally importantly, in the absence of a definitive link between the automobile emissions inspection indicator variable and the hypothesized indications discussed previously – namely, the GHG reducing policies indication and the environmentally favorable travelers' attitudes and behaviors indication – along with the inability of the inspection proxy variable to distinguish between the two on its own, the discussed effects of all the considered variables are worthy of further investigation as part of future research.

Certain explanatory variables that are not included in the estimated model shown in Table 2 were also considered and their estimated coefficients were found not to be statistically significant in either emissions inspection model segment. For example, an alternate definition of transit share that does not take into account the passenger distance traveled, namely the simple ratio of transit passenger trips to total trips, was considered. When using the latter definition, the resulting estimated coefficients are found not to be statistically significant whether in the presence of vehicle inspection or not. This result highlights the importance of considering passenger distances traveled to effectively capture the role increased transit use plays in reducing CO<sub>2</sub> emissions. Surprisingly, transit service utilization is found not to have a statistically significant role. It is expected that a well-utilized transit system would contribute to reducing  $CO_2$  per capita, but the data do not support this hypothesis. The values of transit service utilization among the 146 urbanized areas only range from 0.023 to 0.273 and the correlation of transit service utilization with  $CO_2$  per capita is only -0.091, which help explain why the estimated coefficients of transit service utilization are found not to be statistically significant when this variable is considered as an explanatory variable in both segments of the model. A log transformation of this variable was also considered to widen its range, but the corresponding estimated coefficients were still found not to be significant. In addition to population density, the coefficient of variation (CV) of population density was considered. Unlike the finding in Southworth and Sonnenberg (2011), where the estimated coefficient of a variable that measures the extent to which the population is evenly distributed across a metropolitan area is found to be statistically significant, the estimated coefficients of CV of population density are found not to be significant in this study. This lack of statistical significance could be a result of the crude nature of the calculation of CV where zip the code sectors used for this purpose may be too aggregate to capture CV effectively.

In the same manner that the variables mentioned above are not included in the model estimation results presented in Table 2, it would be appropriate to exclude the variables whose estimated coefficients are not found to be statistically significant exclusively under either the presence of emissions inspection programs, especially in the cases where the estimated coefficients are not only found not to be statistically significant but also exhibit counterintuitive signs (this combination applies to the estimated coefficients of transit share in the presence of inspection and of 1/Density in the absence of inspection). However, estimation

results where such omissions are applied are not presented in this report to maintain consistency with the testing of the significance of the differences between the estimated coefficients in the presence and absence of inspection discussed previously.

## **3. NEXT STEPS**

It would be worthwhile to use the estimated segmented model where selectively bias is corrected for to quantify the impacts of hypothetical changes in the various variables on  $CO_2$  emissions for select urbanized areas spanning the range of  $CO_2$  emissions per capita, population sizes, and falling in the two automobile inspection program categories. In addition, it is important to identify the policy implications of the quantified impacts. Specifically, in would be valuable to identify the variables that have the most impact on changing  $CO_2$  emissions, explore the comparative impacts of the various variables, and probe the value and limitations of the developed model for the purpose of policy-making. More broadly, the role and use of such a model in understanding the interactions between policy and travel behavior and, consequently, in policy-making clearly warrant further investigations.

## 4. REFERENCES

- 1. Almanac of Policy Issues, 2002. Plain English Guide To The Clean Air Act. URL: http://www.policyalmanac.org/environment/archive/epa\_clean\_air\_act.shtml.
- 2. Center for Climate and Energy Solutions, 2011. Vehicle Greenhouse Gas Emission Standards. URL: http://www.c2es.org/us-states-regions/action/california/vehicle-ghg-standard.
- 3. DieselNet, 2011. United States Emmissions Standards. URL: http://www.dieselnet.com/ standards/us/.
- 4. Energy Information Administration, 2008. Emissions of Greenhouse Gases in the United States 2007. Report No. DOE/EIA-0573, Washington, D.C.
- 5. Gaker, D., Vautin, D., Vij, A., Walker, J. L., 2011. The power and value of green in promoting sustainable transport behavior. Environmental Research Letters, 6(3), 034010.
- Jariyasunant, J., Abou-Zeid, M., Carrel, A., Ekambaram, V., Gaker, D., Sengupta, R., Walker, J., 2014. Quantified Traveler: Travel Feedback Meets the Cloud to Change Behavior. Journal of Intelligent Transportation Systems, http://www.tandfonline.com/ doi/abs/10.1080/15472450.2013.856714.
- 7. Mannering, F, 1987. Selectivity Bias in Models of Discrete and Continuous Choice: An Empirical Analysis. Transportation Research Record 1085, 58-62.
- Mishalani, R. G., Goel, P. K., 2011. Impact of Public Transit Market Share and other Passenger Travel Variables on CO<sub>2</sub> Emissions: Amassing a Dataset and Estimating a Preliminary Statistical Model. NEXTRANS Report, Project No. 035OY02, University Transportation Center, Research and Innovative Technology Administration, U.S. Department of Transportation.

- 9. Mishalani, R. G., Goel, P. K., 2015. Impact of Public Transit Market Share and other Transportation Variables on GHG Emissions: Developing Statistical Models for Aggregate Predictions. NEXTRANS Report, Project No. 0630Y03, University Transportation Center, Research and Innovative Technology Administration, U.S. Department of Transportation.
- Rilett, J, 2002. GHG Reduction in Road Transportation: A Scoping Report into Vehicle Inspection/Maintenance Programs and Alternatives in Alberta. Climate Change Central, Calgary, AB.
- 11. Southworth, F., Sonnenberg, A., 2011. Set of Comparable Carbon Footprints for Highway Travel in Metropolitan America. Journal of Transportation Engineering 137(6), 426-435.
- 12. US Environmental Protection Agency, 2012. *Emissions Inventories*. URL: http://www.epa.gov/ttn/chief/eiinformation.html.
- 13. Washington, S., Karlaftis, M., Mannering, F., 2003. Statistical and Econometric Methods for Transportation Data Analysis. Boca Raton, FL: Chapman & Hall.