Spatial Transferability: Analysis of the Regional Automobile-Specific Household-Level Carbon Dioxide (CO_2) Emissions Models

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This paper compared performance of methods for combining model information estimated in one region and applied to another region to improve estimation results. The application is for models developed to estimate household-level automobile-specific CO_2 emissions. The results indicated that automobile-specific CO_2 emissions models can be transferred from one geographical region to another. The estimates of CO_2 emissions can assist agencies such as policy makers, businesses, and transportation planners to track trends and identify opportunities to reduce CO_2 emissions and increase efficiency of transportation systems to lessen their impact on global warming, climate change, and air quality standards.

INTRODUCTION

The primary determinants of household-level carbon dioxide (CO_2) emissions produced from vehicle sources are fuel carbon content, vehicle fuel efficiency, and vehicle miles traveled (USDOT 2009, Chiou et al. 2009). Vehicle tailpipe carbon dioxide emissions contribute about 95% of total carbon dioxide emissions produced from transportation sector-related sources. In an effort to reduce emissions, most transportation and planning agencies are required by state and local governments to forecast the amount of emissions and propose strategies and policies for reducing the carbon dioxide in their regions. One of the approaches used to accomplish this is the development of statistical models to estimate the amount of the CO_2 emissions and then use the models to forecast future emissions. The models incorporate factors that influence vehicle travel to provide the estimates of CO_2 emissions produced per modeling unit selected, e.g., per trip. In other words, the models determine the magnitudes and patterns of various variables that capture characteristics related to socioeconomic, demographic, land use, and transportation systems of a region on vehicle travel (Chiou et al. 2009, Brownstone and Golob 2009). Most states and local governments require estimation of CO_2 emissions and other greenhouse gases to track trends of CO_2 emissions in their regions. The main objective is to reduce the impact of CO_2 emissions on global warming, climate change, and air quality standards. The estimates help policy makers, businesses, and transportation planners to evaluate current policies and propose future alternatives to improve efficiency of transportation systems and reduce CO_2 emissions.

Most of the models for predicting CO_2 emissions are estimated using cross-sectional data. The applications of such models are twofold. Firstly, the models can be applied to forecast the amount of CO_2 emissions produced in the same region but at different time periods based on extrapolation of cross-sectional variations. This type of application is referred to as "temporal transferability" of the models. Secondly, the models estimated from one geographic region can be applied to estimate CO_2 emissions in a different geographic region. This type of application is referred as "spatial transferability" of the models.

The potential benefits of the spatial transferability of the models cited in the literature include reduction and/or elimination of large data collection and model development efforts in the application region (Karasmaa 2007). Application region refers to a region where data and/or parameters were applied from another region, whereas estimation region refers to a region where data were collected and/or parameters were estimated. In addition, the spatial transferability of the models is more important to the application regions, which have limited data for estimation, evaluation, and prediction of the impacts of CO_2 emissions on air quality, climate change, and global warming. This is potentially very useful for small regions or communities that would like to quickly/easily estimate CO_2 emissions from vehicle use but do not have adequate data for developing their own model. The transfer methods can incorporate model information from other regions to make up for the local data shortfall. Additionally, the growing interest for integrating climate change into the transportation planning process to reduce the impacts of greenhouse gas emissions on global warming, climate change, and air quality conformity also highlights the importance and potential of the spatial transferability of regional household-level CO_2 emissions models (FHWA 2008).

In the literature, current empirical studies have mainly focused on establishing a relationship between CO_2 emissions and different attributes of socioeconomic, demographic, and land use variables. However, very limited research studies have been done to evaluate spatial transferability and prediction performance of regional household-level automobile-specific CO_2 emissions models formulated using cross-sectional data. To address this limitation, the primary objectives of this paper are as follows:

1. To analyze the potential of spatial transferability of regional household-level automobile-specific CO_2 emissions models. In this paper, the regional household-level CO_2 emissions models are developed for four regions in the U.S., namely, Northeast, Midwest, South, and West. These four regions were selected because they are included in the National Household Travel Survey (NHTS) datasets and provide opportunity to analyze the effect of sample size on the spatial transferability of the models. In this analysis, a model developed for each region is transferred to predict automobile-specific household-level CO_2 emissions in the other regions. In addition, a national CO_2 emissions model is developed and transferred to predict CO_2 emissions of the four regions.
2. To evaluate different methods for transferring travel data or parameters of a model from one geographical region to another and their prediction performance for the models developed in objective one (1) above.

Although significant changes have occurred since the mid-1990s in terms of vehicle travel, as of today the automobile is still the dominant travel mode in the United States. Also, most cars still use gasoline. This suggests that CO_2 emissions generated from household vehicles is still a major problem that needs to be addressed to reduce CO_2 impact on global warming, climate change, and air quality.

LITERATURE REVIEW

A review of literature on the amount of CO_2 produced from vehicle emissions revealed that several previous studies have attempted to develop a relationship that exists between socio-economic, land use, and transport systems and CO_2 emissions (Grane 2000, Ewing and Cervero 2001, Handy et al. 2005, Newman and Kenworthy 1989, Stead 1999). The most recent studies have also continued to investigate the relationship between CO_2 emissions as a function of land use patterns and travel behavior (Bento et al. 2005, Geurs and Wee 2006). The majority of these empirical studies agree that densification of land use measured in terms of housing units per square mile reduces vehicle miles of travel, energy consumption, and emissions (Stone et al. 2007, TRB 2009). In other words, regions with high housing units per square mile produce less CO_2 emissions compared with similar regions with low housing units per square mile. Another study by Akisawa and Kaya (1998) investigated the optimal land use in urban areas that would minimize energy consumption in transportation. This study concluded that minimum energy consumption occurs when business areas are located around the center of a city, whereas residential areas are located in suburbs.

Furthermore, some of the past studies have used disaggregate travel data to establish the relationship between attributes of land use, household, and vehicle use (Chiou et al. 2009, Brownstone and Golob 2009, Bento et al. 2005, Boussauw and Wiltox 2009). Similarly, these studies indicated that land use density directly influences vehicle usage, which in turn influences fuel consumption and emissions. For example, a study by Boussauw and Witlox (2009) indicated that vehicle energy performance increases with land use density. In addition to land use density, studies also have shown that residents residing in rural areas produce more carbon dioxide emissions per trip than urban or suburban households (USDOT 2009). This is could be partly due to rural residents driving relatively longer trips to service locations with less fuel-efficient vehicles than urban residents. A most recent study by Mwakalonge et al. (2012) evaluated prediction performance of carbon dioxide emission models.

Notwithstanding significant research efforts on estimation and prediction of CO_2, still very limited studies have evaluated the significance and importance of spatial transferability of the models. Siuhi et al. (2012) empirically assessed the spatial transferability of CO_2 emissions models using the 2009 National Household Travel Survey (NHTS) dataset. This study focused on a single pair of cities in one state. This was a major limitation of the analysis because the two cities shared similar populations, urban form, and climate and are of modest size. In other words, the study focused the analysis on a case of two cities within the same state and in relatively close proximity. Using a single pair of cities is unlikely to provide general insight and justification for other dissimilar pairs of cities. Thus, analysis of more pairs of regions or cities would warrant a justification for transferability of travel data or parameters of a model estimated from one region and applied to another region to improve prediction performance.

SPATIAL TRANSFERABILITY METHODS

This paper evaluates four transfer methods which are commonly used to transfer model parameters and/or travel data from one geographical region to another. In the literature, several empirical studies have evaluated different methods used for spatial transferability of model parameters and their predictive performance (Karasmaa 2007, Atherton and Ben-Akiva 1976, Badoe and Miller 1995a and 1995b, Koppelman and Wilmot 1982, Mohammadian and Zhang 2007, Zhang and Mohammadian 2008). The transfer methods evaluated include Naïve Transfer, Joint Context Estimation, Bayesian Updating, and Combined Transfer Estimator. These past studies have applied these methods to spatially transfer trip-generation and mode choice models. On the other hand, a recent study by Siuhi et al. (2012) also attempted to apply these four transfer methods to spatially transfer CO_2 emissions model between a pair of cities within one state. As stated earlier, applying the transfer methods for only a single pair of cities within one state does not provide sufficient information on whether the methods can be applied to other disparate pairs of cities or regions to produce similar results. The following subsection briefly discusses the transfer methods evaluated in this research.

Naïve Transfer

The Naïve Transfer method involves a transfer of model parameters estimated from one region to predict CO_2 emissions of another region while completely ignoring local travel data. For instance, the model parameters calibrated using the Northeast region is used to predict CO_2 emissions of the Midwest region without making any modifications. Application of this method assumes that socioeconomic, demographic, land use, transport systems, and other relevant factors that affect CO_2 emissions in the estimation region and application region are the same, which may be unrealistic. This implies that model parameters estimated from the estimation region can be used in the application region without any further modification. In other words, parameters of the estimation region are used in the application region while completely ignoring the travel data from the application region. Mathematically, this transfer of parameters is done by applying restrictions on the specified model as shown in Equation 1. The subscript i refer to estimation region while the subscript j refers to application region.

(1) $\boldsymbol{\beta_i} = \boldsymbol{\beta_j} = \boldsymbol{\beta}$ and $\lambda_i = \lambda_j = \lambda$

Where:

$\boldsymbol{\beta_i}$ is the vector of parameters from the estimation region
$\boldsymbol{\beta_j}$ is the vector of parameters of the application region
λ_1 is the constant term from the estimation region
λ_2 is the constant term from the application region

The least squares estimator $\boldsymbol{\beta}$ of the unknown vector of parameters of the model parameters is estimated as follows:

(2) $\boldsymbol{\beta} = (\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{Y}$

Where:

Y is the vector of response variable from the estimation region.
X is the matrix of explanatory variables from the application region
$\mathbf{X}^{\mathbf{T}}$ is the transpose of a matrix X

In practice, however, this is unrealistic and the assumption put forth is too strong to justify its validity, hence, transferability of the model is done with inclusion of travel data collected from the application region.

Joint Context Estimation

This method combines the datasets from the estimation region and application region to estimate parameters of the application region. For example, combined data from the south region (referred to as estimation region) and west region (referred as application region) are combined to estimate the parameters of the west region. This method assumes acceptance of the homogeneity hypothesis of the parameters from the estimation region and application region. Therefore, the true model parameters governing CO_2 emissions and their error variance are the same across space or spatially. In other words, the method assumes neither the observed factors known to impact the CO_2 emissions specified in the model nor that the unobserved factors are different across the two regions. For a detailed discussion about this method from past studies see Ben-Akiva and Morikawa (1990), Bradley and Daly (1991), and Ben-Akiva and Bolduc (1987). In this paper, datasets from the estimation region and application region are combined to yield the parameters used to predict CO_2 emissions of the application region. This is done by imposing restrictions on the specified model as shown below.

(3) $\boldsymbol{\beta_i} = \boldsymbol{\beta_j} = \boldsymbol{\beta}$ and $\lambda_i = \lambda_j = \lambda$

Where:

$\boldsymbol{\beta_i}$ is the vector of parameters of the estimation region

$\boldsymbol{\beta}_j$ is the vector of parameters of application region
λ_1 is the constant term of the estimation region
λ_2 is the constant term of the application region

The least squares estimator $\boldsymbol{\beta}$ of the unknown vector of parameters of the model parameters is estimated as follows:

(4) $\boldsymbol{\beta} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$

Where:

$\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_i \\ \mathbf{Y}_j \end{bmatrix}$ is the vector of response variables from the estimation and application regions, respectively.

$\mathbf{X} = \begin{bmatrix} \mathbf{X}_i \\ \mathbf{X}_j \end{bmatrix}$ is the matrix of explanatory variables from the estimation and application regions, respectively.

$\mathbf{X}^T$ is the transpose of a matrix $\mathbf{X}$

Bayesian Updating

This transferability method was introduced by Atherton and Ben-Akiva (1976). The Bayesian Updating method estimates parameters of the application region based on the combined parameter estimates from the estimation region and application region. Unlike the Joint Context Estimation method, which directly combines the datasets from the estimation and application regions, this method combines the parameters of the two regions to yield unbiased parameters of the application region. The method uses traditional Bayesian analysis, assuming the two regions share the same set of parameters that are unbiased estimators of the true parameters of the application region. This method is expressed mathematically as follows:

(5) $\hat{\boldsymbol{\beta}}_{BU} = \left(\boldsymbol{\Sigma}_i^{-1} + \boldsymbol{\Sigma}_j^{-1}\right)^{-1} \left(\boldsymbol{\Sigma}_i^{-1}\,\hat{\boldsymbol{\beta}}_i + \boldsymbol{\Sigma}_j^{-1}\,\hat{\boldsymbol{\beta}}_j\right)$

Where:

$\boldsymbol{\beta}_{BU}$ is the transferred parameters of the application region
$\boldsymbol{\beta}_i$ is the estimated parameters from the estimation region
$\boldsymbol{\beta}_j$ is the estimated parameters from the application region
$\boldsymbol{\Sigma}_i$ is the covariance matrix of the estimation region
$\boldsymbol{\Sigma}_j$ is the covariance matrix of the application region

The corresponding covariance matrix is estimated as follows:

(6) $\boldsymbol{\Sigma}_{BU} = \left(\boldsymbol{\Sigma}_i^{-1} + \boldsymbol{\Sigma}_j^{-1}\right)^{-1}$

Where:

Σi is the covariance matrix of the estimation region
Σj is the covariance matrix of the application region

Combined Transfer Estimator

This transfer method is a generalization of the Bayesian Updating method. Unlike Bayesian Updating, which ignores transfer bias, this method takes into consideration transfer bias effects on the transferred parameters (Karasmaa 2007, Koppleman and Wilmot 1982, Ben-Akiva and Bolduc 1987). Transfer bias is defined as the difference between the parameter of the estimation and application region ($\beta_1 - \beta_2$). The basic theory of this method is that the contribution of the parameters of the estimation region to the application region decreases as transfer bias increases. On the contrary, the contribution of the estimation region to the application region increases as the transfer bias decreases. This is expressed mathematically as shown below.

$$(7)\quad \hat{\boldsymbol{\beta}}_{\mathrm{CTE}} = \left(\left(\boldsymbol{\Sigma}_{\mathrm{i}}^{-1} + \Delta\Delta^{\mathrm{T}}\right)^{-1} + \boldsymbol{\Sigma}_{\mathrm{j}}^{-1}\right)^{-1} + \left(\left(\boldsymbol{\Sigma}_{\mathrm{i}}^{-1} + \Delta\Delta^{\mathrm{T}}\right)^{-1} \hat{\boldsymbol{\beta}}_{\mathrm{i}} + \boldsymbol{\Sigma}_{\mathrm{j}}^{-1}\,\hat{\boldsymbol{\beta}}_{\mathrm{j}}\right)$$

Where:

$\mathbf{B}_{\mathrm{CTE}}$ is the transferred parameters of the application region
$\boldsymbol{\beta}_{\mathbf{i}}$ is the estimated parameters from the estimation region
$\boldsymbol{\beta}_{\mathbf{j}}$ is the estimated parameters from the application region
$\boldsymbol{\Sigma}_{\mathbf{i}}$ is the covariance matrix of the estimation region
$\boldsymbol{\Sigma}_{\mathbf{j}}$ is the covariance matrix of the application region
$\Delta = (\beta_1 - \beta_2)$ is the transfer bias
Δ^T is the transpose of a matrix Δ

The corresponding covariance matrix is computed as follows:

$$(8)\quad \Sigma_{\mathrm{CTE}} = \begin{pmatrix} \Sigma_{\mathrm{i}}^{2} & 0 \\ 0 & \Sigma_{\mathrm{j}}^{2} \end{pmatrix}$$

Where:

$\boldsymbol{\Sigma}_{\mathbf{i}}$ is the covariance matrix of the estimation region
$\boldsymbol{\Sigma}_{\mathbf{j}}$ is the covariance matrix of the application region

The model transferability methods discussed above differ from each other mainly on how they incorporate datasets from the estimation region and application region to produce parameters of the transferred model or application region. In summary, all transfer methods attempt to minimize the variance of parameters of the transferred model of the application region that has a relatively small sample. A small sample of the estimation region travel data causes an increase in variance of parameters of the model, which is also reflected in the transferred model as well (Karasmaa 2007). To determine sample size from the estimation region that produces the best parameters of the transferred parameters requires evaluating prediction performance for various combinations of datasets of the estimation and application regions. In this research, prediction performances were evaluated using two measures discussed in detail in the next section.

MODEL SPECIFICATION AND ESTIMATION

This paper specified two multivariate functional form models, namely, linear ordinary least squares and exponential. Unlike the linear model, the exponential form restricts prediction of nonnegative CO2 emissions values. The parameters of the models were estimated and the best model was selected for further analysis based on R-squared (R^2) goodness-of-fit measure. In this paper, R^2 (coefficient of determination) measures how well a model explains and predicts outcomes of the estimated CO_2

emissions. The exponential functional form produced the highest R^2 measure compared with the linear ordinary least squares model. The final formulation of the exponential model is as follows:

$$(9) \quad y_h = e^{\beta_0 + \sum_{j=1}^{N} \beta_j X_{hj} + \varepsilon_h} \qquad \forall_j = 1,2,3,..., \text{N}$$

Where:

h indexes household observations
j indexes the explanatory variables
y_h is the annual total CO_2 emissions in kilograms produced by household h
X_{hj} is the k^{th} explanatory variable of household vehicle j
β_j is the k^{th} coefficient of the k^{th} explanatory variable
ε_h is the random term for household h, and
β_0 is the constant term
N is the total number of explanatory variables

The parameters of the model specified in Equation 1 were estimated using the nonlinear least squares regression technique. In a nonlinear model, the unknown parameters of the models are estimated by maximizing the log likelihood function. This paper used the Stata program nonlinear command "nl" to estimate parameters of the model. The Stata implements a modified Gauss-Newton method in estimating parameters of the models. Selection of explanatory variables for inclusion in the model was primarily done based on correlation analysis and analysis of variance. Final variables specified were the ones that exhibited higher correlation with the estimated CO_2 emissions (i.e., response variable) but with lower degree of correlation to each other. This was done to prevent multicolinearity and over-specification of the model.

Measures for Assessing Prediction Performance of Transfer Methods

Transfer R-squared (R^2) and Transfer Index (TI) are two measures that are used in this paper to assess prediction performance of the transferred models. The measures indicate how well a transferred model predicts the estimated CO_2 emissions in the application region. These measures have been widely used in past studies to assess prediction performance of model transferability (Karasmaa 2007, Ben-Akiva and Morikawa 1990, Badoe and Steuart 1997). Ideally, the measures are used to assess the prediction performance of transferred parameters from the estimation region for predicting CO_2 emissions of the application region. Transfer R^2 value, denoted as R^2_{ij}, indicates the ability of the parameters of the estimation region in explaining the variations of CO_2 emissions of the application region. As indicated earlier, subscript i refers to the estimation region while the subscript j refers to the application region. Mathematically, Transferred R^2 is defined as follows:

$$(10) \quad R^2{}_{ij} = \frac{SSE_{ij}}{SST_{jj}}$$

Where:

SSE_{ij} is the explained or regression sum of squares obtained by predicting the calculated CO_2 emissions in the estimation region using parameters from the application region
SST_{jj} is the total sum of squares obtained by predicting CO2 emissions in the application region

Transfer Index (TI_{ij}) is a relative measure which measures how good the parameters from the estimation region predicts the corresponding observed CO_2 emissions in the application region relative to the parameters estimated using local region travel data. It is expressed mathematically as follows:

$$(11)\quad TI_{ij} = \frac{R^2{}_{ij}}{R^2{}_{jj}}$$

Where:

$R^2{}_{ij}$ is the R^2 value obtained by predicting the calculated CO_2 emissions in the estimation region using parameters from the application region

$R^2{}_{jj}$ is the R^2 obtained by predicting the observed CO_2 emissions of the estimation region based on parameters estimated using application region data

DATA SOURCE

Data for the study came from 2009 National Household Travel Survey (NHTS) conducted by the U.S. Department of Transportation (USDOT 2009). This is a nationally representative survey of travel behavior conducted from April 2008 through April 2009. The data gathered trip-related information such as mode of transportation, duration, distance, and purpose. It then connected this travel related information to demographic, geographic, and economic factors for analysis. During the survey period, each household was sent a travel diary and asked to report all travel by household members on a randomly assigned "travel day." Interviewers followed up with a phone call that collected detailed information about their travel from each household member. Travel days for daily-travel trip reporting were assigned for all seven days of the week, including holidays. Data were weighted to correctly reflect the day of week and month of travel to allow comparisons of weekdays or seasons. The total sample size was 150,147 households, which consists of 25,000 nationwide and 125,147 obtained from 20 add-on areas, mainly state departments of transportation (DOTs) and metropolitan planning organizations (MPOs). The data were further expanded to provide national estimates of trips and miles of travel by travel mode, trip purpose, and other household characteristics. The survey is documented in detail at http://nhts.ornl.gov/. A major limitation of the NHTS Travel Day Survey is that it did not take into account longer-term trips (e.g., longer than 24 hours). However, most of the longer trips were inter-regional and therefore viewed as is inappropriate for an intra-regional analysis, which is the focus of this paper.

Method for Determining CO2 Emissions

The amount of CO_2 emissions associated with fuel combustion are a function of the volume of fuel combusted, density of the fuel, carbon content of the fuel, and fraction of carbon that is oxidized to CO_2 (EPA 2008). The NHTS dataset does not contain estimates of CO_2 emissions but has variables that can be used for estimating the amount of CO_2 emissions produced by combustion of different types of fuels. This paper estimated CO_2 emissions taking into consideration emission rates per gallon, amount of gallons consumed, vehicle miles of travel, and vehicle fuel efficiency in three steps as follows:

Step 1: Determining Emission Rates Per Gallon of Fuel

The amount of CO_2 created from combusting one gallon of fuel depends on the amount of carbon in the fuel. After combustion, a majority of the carbon is emitted as CO_2 and very small amounts of hydrocarbons and carbon monoxide. Carbon content varies by fuel, and some variation within each type of fuel is normal. The Environmental Protection Agency (EPA) and other agencies use the following average carbon content values to estimate CO_2 emissions (EPA 2008):

CO_2 emissions from gasoline: 8.887 kilograms per gallon

CO_2 emissions from diesel: 10.180 kilograms per gallon

CO_2 emissions from natural gas: 6.900 kilograms per gallon

The assumption put forth with respect to electric vehicles in this paper is that on-road "tailpipe" CO_2 emissions produced are negligible. This assumption, however, is unrealistic when evaluating CO_2 emissions on the life cycle basis.

Step 2: Determining Annual CO_2 Emissions of Each Household Vehicle

The annual CO_2 emissions emitted by each household vehicle are a function of a type of fuel, fuel economy of a vehicle, and number of miles driven a year. Thus, the total amount of CO_2 emissions produced over a year of driving a certain type of vehicle is estimated as follows:

$$(12)\quad Annual\ CO_2\ emissions\ (kg) = \frac{CO_2\ per\ gallon}{miles\ per\ gallon} \times miles\ driven$$

Step 3: Determining Annual CO_2 Emissions Emitted by a Household

The amount of CO_2 emissions produced by a household varies based on number of vehicles the household has driven over a year. The total annual amount of CO_2 emissions is the sum of emissions for all household vehicles and estimated as follows:

$$(13)\quad Total\ annual\ CO_2\ emissions\ (kg) = \sum_{j=1}^{N} Annual\ CO_{2\,j}$$

Where N is the total number of household vehicles and j is the household vehicle.

Table 1 shows a summary of variable codes and their corresponding descriptive statistics for the national, Northeast region, Midwest region, South region, and West region datasets.

ANALYSIS AND DISCUSSION OF RESULTS

Tables 2 through 5 show the results of the four transfer methods for different estimation and application regions. As discussed earlier, the transfer methods are Naïve, Joint Context Estimation (JCE), Bayesian Updating (BU), and Combined Transfer Estimator (CTE). Similarly, the four regions included in this analysis are Northeast, Midwest, South, and West. The tables show the number of observations in each region, coefficient (*coef.*), and t-statistic (*t-stat.*), and transfer R^2. The *t-stat* is used to measure statistical significance of the variables at 5% level. On the other hand, transfer R^2 measures how well the transferred model from the estimation region explains variation of CO_2 emissions in the application region.

The sign of the coefficient of population density variable (popden) is negative for all models presented in Tables 2 through 5. The negative sign indicates, all being equal, a land use that has more population per square mile produces significantly more CO_2 emissions per year compared with a similar land use with less population per square mile. This is consistent with what one would expect for this variable. This could be partly associated with residential location decisions relative to employment and public service areas. Residents residing in land uses with higher population density are likely to be closer to employment services relative to those who live in lower density,

Table 1: Variable Codes and Descriptive Statistics

National			
Codes	*Descriptions*	*Mean*	*Standard Deviation*
CO2	Annual total household CO_2 emissions (kg)	8627	8382
popden	Population density per mi^2 (in 1,000) (tract-level)	2.97	4.27
hhsize	Number of household members	2.41	1.24
vehcnt	Number of household vehicles	2.18	1.108
income	Total household income (in 1,000)	57.60	31.27
Northeast Region			
CO2	Annual total household CO_2 emissions (kg)	7799	7129
popden	Population density per mi^2 (in 1,000) (track-level)	3.28	6.14
hhsize	Number of household members	2.43	1.23
vehcnt	Number of household vehicles	2.07	1.04
income	Total household income (in 1,000)	60.0	30.85
Midwest Region			
CO2	Annual total household CO_2 emissions (kg)	9004	9128
popden	Population density per mi^2 (in 1,000) (tract-level)	2.08	2.80
hhsize	Number of household members	2.43	1.27
vehcnt	Number of household vehicles	2.29	1.17
income	Total household income (in 1,000)	55.36	29.7
South Region			
CO2	Annual total household CO_2 emissions (kg)	8973	8793
popden	Population density per mi^2 (in 1,000) (tract-level)	2.11	2.84
hhsize	Number of household members	2.37	1.20
vehcnt	Number of household vehicles	2.18	1.07
income	Total household income (in 1,000)	56.04	31.40
West Region			
CO2	Annual total household CO_2 emissions (kg)	8046	7497
popden	Population density per mi^2 (in 1,000) (tract-level)	5.47	5.39
hhsize	Number of household members	2.50	1.33
vehcnt	Number of household vehicles	2.19	1.16
income	Total household income (in 1,000)	61.31	31.54

hence making comparatively shorter trips per year than their counterparts. Additionally, most people put considerable weight on travel costs in their location decisions and reside fairly closer to the employment locations (Badoe and Steuart 1997). This translates to shorter travel distance per year and less CO_2 emissions than in areas with lower employment density.

The sign of the coefficient of household size variable (hhsize) is positive for all models. This is an indication that a household with many members releases significantly more CO_2 emissions than a household with fewer members. These results make sense because families with many members are expected to participate in many activities per year relative to households with fewer members. This contributes to longer cumulative annual traveled distances and more CO_2 emissions. Similarly, the sign of the coefficient of number of household vehicles variable (vehcnt) is positive across all models. This indicates, on average, a household that owns many vehicles produces comparatively more CO_2 emissions than a household with fewer vehicles per year. The reason for this result is similar to the one given for the household size. The sign of the coefficient of household income variable (income) is positive for all models. This implies that a high-income household produces significantly more CO_2 emissions than a low-income household per year. This is logical because most affluent households reside in less dense areas, which are relatively far from services locations such as shopping centers and hence travel longer distances per year. These results also reflect fuel efficiency of vehicles high-income households own in comparison to low-income households. The expectation is that high-income households are likely to own bigger vehicles (i.e., pickup trucks and SUVs), which have relatively low fuel efficiency than smaller vehicles. This result, however, contradicts with the expectation that high-income households are also likely to own newer vehicles which are subject to stricter regulations and emit less CO_2 emissions per year.

Tables 2 through 5 also indicate statistical significance of the variables measured in terms of t-statistic (t-stat). The critical t-statistic at the 5% significance level is 1.96. Comparing t-statistic results shown in Tables 2-5, it is evident that all variables are statistically significant at the 5% level (i.e., estimated t-statistics are greater than the critical t-statistic). This is an indication that there is statistical evidence that the variables are different from zero at the 5% level. As can be seen from Tables 2 through 5, transfer R^2 values range from 0.4598 to 0.6844. The values explain how well the models transferred from the estimation region explain variations of predicted CO_2 emissions in the application region.

Table 2: Naïve Transfer Results

Estimation Region	Application Region	Northeast		Midwest		South		West	
	No. obs.	17,203		13,721		72,298		27,544	
	Variable	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*
National	const	8.2427	1207.73	8.2427	1207.73	8.2427	1207.73	8.2427	1207.73
	popden	-0.0324	-44.60	-0.0324	-44.60	-0.0324	-44.60	-0.0324	-44.60
	hhsize	0.1151	85.43	0.1151	85.43	0.1151	85.43	0.1151	85.43
	vehcnt	0.0049	65.25	0.0049	65.25	0.0049	65.25	0.0049	65.25
	income	0.1428	197.21	0.1428	197.21	0.1428	197.21	0.1428	197.21
	Transfer R^2	0.6695		0.6153		0.6276		0.6503	
Northeast	const	8.0779	468.51	8.0779	468.51	8.0779	468.51	8.0779	468.51
	popden	-0.0227	-15.75	-0.0227	-15.75	-0.0227	-15.75	-0.0227	-15.75
	hhsize	0.0984	28.04	0.0984	28.04	0.0984	28.04	0.0984	28.04
	vehcnt	0.0041	20.68	0.0041	20.68	0.0041	20.68	0.0041	20.68
	income	0.2027	70.04	0.2027	70.04	0.2027	70.04	0.2027	70.04
	Transfer R^2	0.6844		0.6203		0.5239		0.5618	
Midwest	const	8.2296	373.84	8.2296	373.84	8.2296	373.84	8.2296	373.84
	popden	-0.0411	-12.32	-0.0411	-12.32	-0.0411	-12.32	-0.0411	-12.32
	hhsize	0.0699	15.01	0.0699	15.01	0.0699	15.01	0.0699	15.01
	vehcnt	0.0047	19.02	0.0047	19.02	0.0047	19.02	0.0047	19.02
	income	0.2048	63.66	0.2048	63.66	0.2048	63.66	0.2048	63.66
	Transfer R^2	0.6745		0.6269		0.4598		0.5452	
South	const	8.2699	892.02	8.2699	892.02	8.2699	892.02	8.2699	892.02
	popden	-0.0448	-31.11	-0.0448	-31.11	-0.0448	-31.11	-0.0448	-31.11
	hhsize	0.1189	64.54	0.1189	64.54	0.1189	64.54	0.1189	64.54
	vehcnt	0.0053	52.68	0.0053	52.68	0.0053	52.68	0.0053	52.68
	income	0.1383	145.11	0.1383	145.11	0.1383	145.11	0.1383	145.11
	Transfer R^2	0.6596		0.6144		0.6269		0.6438	
West	const	8.1523	530.19	8.1523	530.19	8.1523	530.19	8.1523	530.19
	popden	-0.0145	-15.02	-0.0145	-15.02	-0.0145	-15.02	-0.0145	-15.02
	hhsize	0.1219	45.64	0.1219	45.64	0.1219	45.64	0.1219	45.64
	vehcnt	0.0046	29.48	0.0046	29.48	0.0046	29.48	0.0046	29.48
	income	0.1328	83.68	0.1328	83.68	0.1328	83.68	0.1328	83.68
	Transfer R^2	0.6718		0.6037		0.6171		0.6569	

Table 3: Joint Content Estimation Results

Estimation Region	Application Region	Northeast		Midwest		South		West	
	No. obs.	17,203		13,721		72,298		27,544	
	Variable	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*
National	const	8.2427	1207.73	8.2427	1207.73	8.2427	1207.73	8.2427	1207.73
	popden	-0.0324	-44.60	-0.0324	-44.60	-0.0324	-44.60	-0.0324	-44.60
	hhsize	0.1151	85.43	0.1151	85.43	0.1151	85.43	0.1151	85.43
	vehcnt	0.0049	65.25	0.0049	65.25	0.0049	65.25	0.0049	65.25
	income	0.1428	197.21	0.1428	197.21	0.1428	197.21	0.1428	197.21
	Transfer R^2	0.6695		0.6153		0.6276		0.6503	
Northeast	const	8.0779	468.51	8.1491	590.83	8.2438	1001.54	8.1484	711.62
	popden	-0.0227	-15.75	-0.0279	-18.8	-0.0386	-34.22	-0.0182	-23.84
	hhsize	0.0984	28.04	0.0851	29.54	0.1182	72.12	0.1178	55.23
	vehcnt	0.0041	20.68	0.0042	26.92	0.0051	56.16	0.0046	37.35
	income	0.2027	70.04	0.2064	96.99	0.1421	165.13	0.1418	109.29
	Transfer R^2	0.6844		0.6246		0.6284		0.6556	
Midwest	const	8.1491	590.83	8.2296	373.84	8.2726	965.78	8.2305	661.67
	popden	-0.0279	-18.8	-0.0411	-12.32	-0.0447	-33.68	-0.0233	-24.13
	hhsize	0.0851	29.54	0.0699	15.01	0.1148	67.03	0.1094	45.81
	vehcnt	0.0042	26.92	0.0047	19.02	0.0053	56.23	0.0046	33.93
	income	0.2064	96.99	0.2048	63.66	0.1412	159.83	0.1434	104.31
	Transfer R^2	0.6822		0.6269		0.6288		0.6539	
South	const	8.2438	1001.54	8.2726	965.78	8.2699	892.02	8.2562	1054.55
	popden	-0.0386	-34.22	-0.0447	-33.68	-0.0448	-31.11	-0.0335	-40.01
	hhsize	0.1182	72.12	0.1148	67.03	0.1189	64.54	0.1184	77.41
	vehcnt	0.0051	56.16	0.0053	56.23	0.0053	52.68	0.005	58.66
	income	0.1421	165.13	0.1412	159.83	0.1383	145.11	0.138	168.64
	Transfer R^2	0.6666		0.6156		0.6269		0.6495	
West	const	8.1484	711.62	8.2305	661.67	8.2562	1054.55	8.1523	530.19
	popden	-0.0182	-23.84	-0.0233	-24.13	-0.0335	-40.01	-0.0145	-15.02
	hhsize	0.1178	55.23	0.1094	45.81	0.1184	77.41	0.1219	45.64
	vehcnt	0.0046	37.35	0.0046	33.93	0.005	58.66	0.0046	29.48
	income	0.1418	109.29	0.1434	104.31	0.138	168.64	0.1328	83.68
	Transfer R^2	0.6751		0.6131		0.6283		0.6569	

Table 4: Bayesian Updating Results

Estimation Region	Application region	Northeast		Midwest		South		West	
	No. obs.	17,203		13,721		72,298		27,544	
	Variable	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*
National	const	8.225	1045.59	8.2465	851.15	8.2521	995.99	8.235	1540.79
	popden	-0.0308	-41.29	-0.0333	-66.05	-0.0356	-49.1	-0.0278	-18.17
	hhsize	0.1146	63.60	0.1126	69.97	0.1165	79.44	0.1158	64.12
	vehcnt	0.0048	45.97	0.0049	62.2	0.005	60.07	0.0048	49.77
	income	0.1466	192.13	0.1459	145.34	0.1413	181.85	0.1414	151.46
	Transfer R^2	0.6722		0.6164		0.6284		0.6522	
Northeast	const	8.0779	468.51	8.1332	392.09	8.2339	859.39	8.1463	439.02
	popden	-0.0227	-15.75	-0.0261	-16.29	-0.0362	-21.74	-0.0183	-27.2
	hhsize	0.0984	28.04	0.0869	23.6	0.1174	45.9	0.1156	38.66
	vehcnt	0.0041	20.68	0.0041	21.71	0.005	35.67	0.0045	25.49
	income	0.2027	70.04	0.2071	59.51	0.1454	132.11	0.1494	85.02
	Transfer R^2	0.6844		0.6240		0.6280		0.6539	
Midwest	const	8.1332	392.09	8.2296	373.84	8.2718	711.47	8.2232	323.52
	popden	-0.0261	-16.29	-0.0411	-12.32	-0.0448	-27.51	-0.0217	-244.63
	hhsize	0.0869	23.6	0.0699	15.01	0.1146	47.38	0.108	38.44
	vehcnt	0.0041	21.71	0.0047	19.02	0.0053	47.24	0.0045	29.87
	income	0.2071	59.51	0.2048	63.66	0.1433	102.33	0.1491	70.74
	Transfer R^2	0.6828		0.6269		0.6287		0.6525	
South	const	8.2339	859.39	8.2718	711.47	8.2699	892.02	8.252	1045.71
	popden	-0.0362	-21.74	-0.0448	-27.51	-0.0448	-31.11	-0.0298	-15.67
	hhsize	0.1174	45.90	0.1146	47.38	0.1189	64.54	0.1185	50.74
	vehcnt	0.005	35.67	0.0053	47.24	0.0053	52.68	0.0049	38.88
	income	0.1454	132.11	0.1433	102.33	0.1383	145.11	0.138	117.44
	Transfer R^2	0.6684		0.6161		0.6269		0.6504	
West	const	8.1463	439.02	8.2232	323.52	8.252	1045.71	8.1523	530.19
	popden	-0.0183	-27.20	-0.0217	-244.63	-0.0298	-15.67	-0.0145	-15.02
	hhsize	0.1156	38.66	0.1080	38.44	0.1185	50.74	0.1219	45.64
	vehcnt	0.0045	25.49	0.0045	29.87	0.0049	38.88	0.0046	29.48
	income	0.1494	85.02	0.1491	70.74	0.138	117.44	0.1328	83.68
	Transfer R^2	0.6768		0.6144		0.6279		0.6569	

Table 5: Combined Transfer Estimator Results

Estimation Region	Application Region	Northeast		Midwest		South		West	
	No. obs.	17,203		13,721		72,298		27,544	
	Variable	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*	*Coef.*	*t-stat*
National	const	8.0781	474.83	8.2296	377.72	8.2698	907.97	8.15247	546.51
	popden	-0.0227	-15.95	-0.041	-12.51	-0.0448	-33.86	-0.0146	-14.67
	hhsize	0.0984	28.38	0.0700	15.21	0.11884	66.78	0.12187	46.33
	vehcnt	0.0041	20.93	0.0047	19.27	0.00534	54.19	0.00462	30.01
	income	0.2026	71.29	0.2047	64.43	0.13831	149.71	0.13285	85.30
	Transfer R^2	0.6840		0.6265		0.6289		0.6565	
Northeast	const	8.0779	468.51	8.229	378.35	8.2699	890.65	8.1523	507.48
	popden	-0.0227	-15.75	-0.0410	-13.78	-0.0448	-30.88	-0.0146	-16.09
	hhsize	0.0984	28.04	0.0701	15.72	0.1189	63.40	0.1219	44.49
	vehcnt	0.0041	20.68	0.0047	19.95	0.0053	51.73	0.0046	28.70
	income	0.2027	70.04	0.2048	62.60	0.1383	144.1	0.1329	81.80
	Transfer R^2	0.6844		0.6265		0.6289		0.6565	
Midwest	const	8.0782	449.55	8.2296	373.84	8.2699	885.86	8.1524	505.65
	popden	-0.0227	-15.4	-0.0411	-12.32	-0.0448	-31	-0.0146	-16.12
	hhsize	0.0983	27.73	0.0699	15.01	0.1188	63.99	0.1219	45.46
	vehcnt	0.0041	20.8	0.0047	19.02	0.0053	52.52	0.0046	29.58
	income	0.2027	67.22	0.2048	63.66	0.1383	143.29	0.1328	81.7
	Transfer R^2	0.6840		0.6269		0.6289		0.6565	
South	const	8.0781	478.28	8.2297	378.73	8.2699	892.02	8.1524	569.15
	popden	-0.0227	-15.65	-0.0411	-12.50	-0.0448	-31.11	-0.0146	-13.24
	hhsize	0.0984	28.40	0.0701	15.23	0.1189	64.54	0.1219	46.46
	vehcnt	0.0041	20.96	0.0047	19.32	0.0053	52.68	0.0046	30.28
	income	0.2026	72.07	0.2047	64.62	0.1383	145.11	0.1328	86.86
	Transfer R^2	0.6840		0.6265		0.6269		0.6565	
West	const	8.078	460.91	8.2296	369.59	8.2699	911.08	8.1523	530.19
	popden	-0.0226	-17.8	-0.041	-13.28	-0.0448	-29.75	-0.0145	-15.02
	hhsize	0.0984	28.97	0.07	15.47	0.1189	62.19	0.1219	45.64
	vehcnt	0.0041	21.14	0.0047	19.6	0.0053	50.84	0.0046	29.48
	income	0.2026	76.51	0.2048	65.31	0.1383	140.51	0.1328	83.68
	Transfer R^2	0.6840		0.6265		0.6289		0.6569	

Table 6 shows the results of Transfer Index (TI), which is used in this research as the measure for assessing prediction performance of the transferred models. From equation 13, TI greater than one means that the transferred model from another region explains variations of the predicted CO_2 emissions better than when compared with a local model. As can be seen from the table, some of the TI values (e.g., bolded) are greater than one which implies that the transferred model better predicts the predicted CO_2 emissions than the local model. For the Northeast region, all transfer methods indicate that the transferred models from the Midwest, South, and West regions produced relatively higher explanation power than the Northeast region. Similar observations are also seen for some of the transferred models in predicting CO_2 emissions in the South and West regions. On the contrary, all transferred models from the Northeast, South, and West to Midwest regions consistently performed poorly in explaining variations of the predicted CO_2 emissions than the Midwest region model. This suggests that factors that influence CO_2 emissions in the Midwest region are somewhat different compared with the Northeast, South, and West regions.

When comparing the four transfer methods, the CTE method produces superior prediction performance based on the transfer R^2 and TI measures as shown in Tables 2 through 6, followed by the other three transfer methods: BU, JCE, and Naïve, in that order. In other words, on the basis of transfer R^2 and TI, the results indicate that the CTE is the best transfer method, followed by BU, JCE, and Naïve. In essence, this pattern reflects how the transferred model incorporates travel data of the application region. It is expected that as transfer bias increases, more weight is assigned to the coefficients of the application region and less weight on the estimation region. These results are in agreement with past studies, which found similar patterns of prediction performance of these transfer methods (Badoe and Steuart 1997). Although the CTE and BU gave superior prediction results as measured in terms of transfer R^2 and TI as shown in Tables 2 through 6, in comparison with the JCE and Naïve transfer methods, they are computationally intractable. The intractability is primarily associated with additional steps required to compute a covariance matrix and/or transfer bias. The analyst, however, should evaluate and decide whether the incremental benefits gained are worth additional computational investment. Overall, the results of the measures of prediction performance demonstrate that the transferred models improved CO_2 emissions prediction performance.

SUMMARY AND CONCLUSION

This paper has empirically analyzed the spatial transferability of the regional automobile-specific household-level carbon dioxide (CO_2) emissions model. The regions considered in this analysis are Northeast, Midwest, South, and West. It also examined prediction performance of model transferability methods, including Naïve, Joint Context Estimation (JCE), Bayesian Updating (BU), and Combined Transfer Estimator (CTE). Prediction performance of the transferred models was assessed in terms of transfer R^2 and Transfer Index (TI). The data used came from the 2009 National Household Survey (NHTS) conducted by the U.S. Department of Transportation. In conclusion, the results indicated that the regional automobile-specific CO_2 emissions model can be transferred from one geographical region to another region and improve prediction performance. This is based on the following observations:

1. All transferred methods consistently indicated that the transferred models from the Midwest, South, and West regions to predict household-level CO_2 emissions in the Northeast region improved prediction performance compared with the Northeast region model. On the other hand, the results indicated that the Midwest region produced better prediction performance compared with the transferred models from the other regions to the Midwest region. This suggests that factors that influence CO_2 emissions in the Midwest region are somewhat different from the Northeast, South, and West regions.

Table 6: Transfer Index (TI) Results

Naïve Transfer				
	Application Region			
Estimation Region	Northeast	Midwest	South	West
National	0.9782	0.9815	**1.0012**	0.9899
Northeast	1.0000	0.9063	0.7655	0.8209
Midwest	**1.0760**	1.0000	0.7334	0.8697
South	**1.0521**	0.9801	1.0000	**1.0270**
West	**1.0227**	0.9190	0.9395	1.0000
Joint Context Estimation				
National	0.9782	0.9815	**1.0012**	0.9899
Northeast	1.0000	0.9127	0.9182	0.9580
Midwest	**1.0882**	1.0000	**1.0031**	**1.0431**
South	**1.0634**	0.9819	1.0000	**1.0361**
West	**1.0276**	0.9333	0.9564	1.0000
Bayesian Updating				
National	0.9822	0.9833	**1.0023**	0.9929
Northeast	1.0000	0.9117	0.9176	0.9554
Midwest	**1.0892**	1.0000	**1.0028**	**1.0408**
South	**1.0662**	0.9827	1.0000	**1.0374**
West	**1.0303**	0.9354	0.9559	1.0000
Combined Transfer Estimator				
National	0.9994	0.9994	**1.0032**	0.9993
Northeast	1.0000	0.9155	0.9189	0.9592
Midwest	**1.0911**	1.0000	**1.0032**	**1.0471**
South	**1.0911**	0.9994	1.0000	**1.0471**
West	**1.0412**	0.9538	0.9574	1.0000

2. Comparison analysis of the transfer methods showed that the CTE produced superior prediction performance as measured in terms of transfer R^2 and TI, followed by other three transfer methods: BU, JCE, and Naïve, in that order. This is a reflection of the effect of incorporating local travel data in the analysis. This is because the CTE method assigns less weight to the parameters of the estimation region when the transfer bias — (e.g., difference between the parameters of the estimation and application regions) is large and vice versa.
3. Even though CTE and BU transfer methods gave superior results in comparison with JCE and Naïve, they are rather computationally intractable. This is primarily due to additional steps required to compute the covariance matrix and/or transfer bias. The modeler/analyst should determine whether the incremental benefits gained are worth additional computational investment.

These results can assist different agencies such as transportation planners to predict automobile-specific CO_2 emissions trends from household-level vehicle travel and identify ways for improving efficiency of transportation systems, and reduce its impact on global warming, climate change, and air quality. The results also can be useful to policy makers and businesses such as the automobile industry to evaluate current and future policies, such as vehicle fuel efficiency standards in order to reduce carbon footprints. The results of this paper are for the spatial transferability of large sub-regions and are unlikely to assist smaller communities. Spatial transferability is crucial to small Metropolitan Planning Organizations (MPOs) that have little travel data for estimation of CO_2 emissions, and future research efforts should address this limitation. In addition, similar analysis should be applied to region-pairs that have different travel behavior or regions where there is a higher proportion of non-automobile travel.

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