Transportation Research Part D 22 (2013) 75–79

Contents lists available at SciVerse ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Residential density and transportation emissions: Examining the connection by addressing spatial autocorrelation and self-selection

Jinhyun Hong *, Qing Shen

University of Washington, Department of Urban Design and Planning, Seattle, WA 98195-5740, United States

ARTICLE INFO

Keywords:
Transportation emissions
Residential density
Confounding by location
Self-selection

ABSTRACT

This paper examines the effect of residential density on CO_2 equivalent from automobile using more specific emission factors based on vehicle and trip characteristics, and by addressing problems of spatial autocorrelation and self-selection. Drawing on the 2006 Puget Sound Regional Council Household Activity Survey data, the 2005 parcel and building database, the 2000 US Census data, and emission factors estimated using the Motor Vehicle Emission Simulator, we analyze the influence of residential density on road-based transportation emissions. In addition, a Bayesian multilevel model with spatial random effects and instrumental variables is employed to control for spatial autocorrelation and self-selection. The results indicate that the effect of residential density on transportation emissions is influenced by spatial correlation and self-selection. Our results still show, however, that increasing residential density leads to a significant reduction in transportation emissions.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

The recent decline in emissions per mile for road transport due to technological advances has been substantially offset by the rapid growth in travel distance. As a response, many urban planners have suggested land use planning as an alternative way to reduce vehicle miles traveled (VMT). While most empirical studies employ statistical models to investigate the relationship between built environments and transportation emissions, there remain two key methodological challenges. First, emissions are often estimated using VMT and emission factors, which do not fully reflect important variations in travel speed and vehicle characteristics. Second, most of these statistical models ignore the influences of spatial autocorrelation and self-selection, which have been shown to create confounding effects on travel behavior. Since transportation emissions are typically computed based on travel outcomes, similar issues can arise in the studies of the relationship between land use and transportation emissions.

This paper incorporates statistical models, which previously addressed the methodological issues of spatial autocorrelation and self-selection separately, into a unified analytical framework for examining the impact of residential density on the emissions of CO_2 equivalent from motorized travel. In this framework, emission factors are estimated to account for diverse characteristics of trips and vehicles, and a Bayesian multilevel model with spatial random effects and instrumental variables

* Corresponding author.
E-mail address: jhhong@uw.edu (J. Hong).

1361-9209/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.trd.2013.03.006

(IVs) is developed. The framework enables us to reexamine the connection between residential density and transportation emissions.

2. Methodology

Transportation emissions are estimated based on VMT per person and diverse emission factors. Because emission factors are sensitive to trip speed and vehicle characteristics, using one generalized emission factor for all trips may result in inaccurate measurements of transportation emissions. Here, emission factors for Pierce County, Washington State, US, based on speed (16 categories), vehicle type (motorcycle, passenger car, passenger truck, school bus, or transit bus), vehicle age, and road type (highway or local roads) are estimated using the Motor Vehicle Emission Simulator (MOVES). This simulator was developed by the US Environmental Protection Agency to estimate air pollution emissions from mobile sources. Its inherent model includes default databases such as vehicle fleet and vehicle activity, although these cannot adequately represent local conditions (US Environmental Protection Agency, 2010). Some of the local data, therefore, collected by the Puget Sound Regional Council (PSRC) is used to obtain more reliable estimates.

Instead of using average speed to estimate transportation emissions, we use road segment speed to estimate road-based transportation emissions. The procedure consists of five steps. First, all trips are categorized into five time periods (am-peak, mid-day, pm-peak, evening and night) to reflect the effects of congestion on speeds on road segments. Second, shortest time path analyses are performed for all trips corresponding to the time periods. Road segment speeds under congested conditions, obtained from PSRC, are estimated using the regional transportation model. Third, using a database management program, route information for each trip is connected to the number of passengers, road segment speed, vehicle characteristics, and road type. Because passenger numbers vary from one bus to another, and across time periods, we adopt the average loadings of 11.29 and 12.59 passengers for off-peak and peak periods provided by the King County Metro Transit (Frank et al., 2011). Fourth, these data are linked with emission factors estimated by MOVES, and road-based transportation emissions per person are calculated by multiplying the road segment length per passenger and the emission factors. Finally, road-based transportation emissions are obtained by aggregating the estimated values for each trip, person, and household.

The multilevel modeling is frequently used in spatial analysis. This model can account for the correlation between elementary units in the same group by introducing varying coefficients, assuming that within neighborhood correlation can capture all spatial autocorrelation (Chaix et al., 2005). Specifically, a multilevel model assumes that two individuals in the same group are correlated by $\sigma_\alpha^2/(\sigma_\alpha^2 + \sigma_y^2)$ while two individuals in different groups are independent. Therefore, the spatial relationship between groups is ignored in the multilevel modeling. To relieve this assumption, we incorporate the spatial random effects (s_j) estimated based on a conditional autoregressive (CAR) model into the Bayesian multilevel framework.

Another strength of this modified framework is that spatial random effects can be viewed as a way to model the effect of location (Clayton et al., 1993). If the spatial patterns of the variations of the independent variable and dependent variable are very similar, the location can be viewed as a confounder and affect the regression coefficient (Clayton et al., 1993; Wakefield, 2003). This is known as "confounding by location." It implies that if there are similar spatial patterns of the variations of residential density and transportation emissions after controlling for other covariates, the effect of residential density on transportation emissions can be mis-estimated due to the unmeasured factors that vary smoothly with location. In sum, the model we use here can consider the influences of unmeasured factors that vary between traffic analysis zones (TAZs) and vary smoothly over TAZs by introducing varying intercepts and spatial random effects, respectively.

In addition, the instrumental variables (IVs) approach is applied to relieve the self-selection impact.[1] If IVs that are uncorrelated with travel attitudes or preferences but associated with built environments exist, the predicted built-environment measure based on these IVs can be used to obtain an unbiased estimate. Neighborhood amenity factors are often used as instruments in the land use–transportation literature.

However, more care should be taken before using the IVs approach in this analysis. First, if a conventional two step approach is employed, then the standard error will be mis-estimated, requiring correction. This is because the predicted variable is used in an isolated manner. This issue can be easily resolved by estimating two steps simultaneously in the Bayesian framework. Second, built-environment measures are spatially correlated. For example, residential density is often employed as the representative of built environments, and it is likely to be positively correlated to neighboring densities. Therefore, incorporating spatial components will improve the explanatory power of the residential density model, leading to the more accurate prediction of residential density. Multilevel model and Bayesian multilevel model with spatial random effects (BMSR) are used to predict residential density and two instruments (percentage of buildings built between 1945 and 1990, percentage of Hispanic population) are employed. In addition, non-informative priors are assigned for all covariates in Winbugs. A BMSR with IVs can be written as:

[1] For details of the concept and other related tests see, Mokhtarian and Cao (2008) and Vance and Hedel (2007).

Download English Version:

https://daneshyari.com/en/article/7501113

Download Persian Version:

https://daneshyari.com/article/7501113

Daneshyari.com