Impacts of Employment Density on Passenger Vehicle Use and Greenhouse Gas Emissions

Technical Background Document

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Study Selection

Many studies over the past two decades have investigated the relationship between land use and travel behavior. The extensive reviews in Parsons Brinkerhoff Quade and Douglas Inc. (1996), Badoe and Miller (2000), Ewing and Cervero (2001), Leck (2006), National Resource Council (2009), Ewing and Cervero (2010) provide detailed overviews of these studies and their evolution over time. However, relatively few studies have specifically investigated the impact of employment density on vehicle miles traveled (VMT).

The research brief includes recent studies (published within the last 10 years) that used disaggregate data on individual travel behavior for one or more U.S. metropolitan areas, employed statistically robust methods that controlled for the impacts of other land use characteristics as well as sociodemographic characteristics, and reported an effect size or enough information in order to compute the elasticity values. Two studies met these criteria: Zhang et al. (2012) and Zhou and Kockelman (2008).

Effect Size, Methodology and Applicability Issues

Many early studies attributed larger impacts on VMT to employment density than recent studies have. This is likely because the earlier studies did not control for the impact of other factors and therefore likely overestimated the impact of employment density.

Zhang et al. (2012) analyzed the impact of land use variables on travel behavior using individual travel survey data for four major U.S. metropolitan areas (Seattle, WA; Richmond-Petersburg and Norfolk-Virginia Beach, VA; Baltimore, MD; and Washington, D.C.). The data used in this study were collected between 2005 and 2009. The study used a Bayesian multilevel model to estimate the effects of employment density and other variables in each metropolitan area. We computed the values of the elasticity of VMT with respect to employment density (defined as the percentage change in VMT for a one percent change in employment density) using the percentage changes reported in the published paper. The elasticity of VMT with respect to employment density was found to be rather modest, with values as follows:

City	Percent VMT Change for 1% Increase in Employment Density
Seattle	-0.0084
Virginia	+0.0125
Baltimore	-0.0114
Washington, D.C.	-0.0015

The positive value for the Richmond-Petersburg and Norfolk-Virginia Beach, VA metropolitan area suggests that higher employment density is associated with *higher* values of VMT.

Similar values were found in the study from Zhou and Kockelman (2008) that analyzed VMT data from households in Austin, TX, through the estimation of linear regression models. The study used travel data collected in the Austin Area Household Travel Survey and land use data provided by the local metropolitan planning organization. The authors estimated separate models for central business district/urban areas and suburban/rural areas. We computed the elasticity of VMT with respect to employment density using the value of the estimated coefficient for employment density from the linear regression models and the values of the mean employment density and VMT for the sample. Given that the coefficient represents the unit change in VMT for a 1 unit change in employment density, elasticity is calculated as follows:

Elasticity = percent change in VMT / percent change in employment density
= (coefficient/mean VMT) / (1/mean density)

Estimates for the elasticity of VMT with respect to employment density are -0.030 in suburban and rural areas and +0.074 in the higher density urban areas, indicating that a further increase in employment density in the latter is associated with a small increase in VMT.

The mix of positive and negative effects coupled with the small magnitudes of the effects in both studies support the conclusion that the effect of employment density on VMT is minimal, at least at the regional level. The reported increases in VMT may stem from competition between jobs and residences for space: as employment density increases, less space is available for residences, and commute distances may increase. The finding by Zhou and Kockelman (2008) of a decrease in VMT in lower density areas but an increase in VMT in higher density areas supports this explanation, as competition for space is greater in higher density areas.

Excluded Studies

Several studies employing meta-analysis methods have provided evidence on the relationships between land use and travel (Ewing and Cervero, 2001; Leck, 2006; Badoe and Miller, 2000; among many others). In contrast with earlier literature reviews, the more recent meta-analyses have adopted more robust statistical approaches that allow for the computation of effect sizes across a set of studies using the datasets from the original studies (e.g. Ewing and Cervero, 2010). However, these analyses run the risk of mixing methodologically flawed studies with methodologically sound studies, thereby contaminating the results of the latter. In addition, meta-analyses suffer from the mixing of “apples and oranges” owing to variation among studies in modeling techniques, independent and dependent variables, and sampling units. Another issue is that studies that show a significant effect are more likely to be published than those that don’t, so that meta-analyses based on published studies may inflate the absolute size of the effects (Ewing and Cervero, 2010).

Many studies have used aggregate data—data for cities, counties, or metropolitan areas rather than for individuals or households—to investigate the relationships between a number of land use variables, including density and travel demand (e.g., Newman & Kenworthy, 1989, 1999, 2006; van de Coevering & Schwanen, 2006). Although these studies allow researchers to expand the investigation to a larger number of areas, and specifically to areas for which disaggregate data are not available, they do not necessarily reveal the actual relationships between land use characteristics and travel behavior. The relationships observed at the city level, for example, may not hold for individuals or households within those cities. For this reason, causal inferences are even more tenuous for aggregate studies than for disaggregate studies. Nevertheless, such studies can yield important insights.

Two recent studies analyzed aggregate data using structural equations models (SEM). SEMs enable the estimation of both direct and indirect relationships among variables and provide a better understanding of the likely causal relationships. A recent study from Lee and Lee (2014) used SEM to analyze the relationships among land use patterns, travel behavior, and CO_2 emissions for 125 medium and large urbanized areas in the United States. This analysis focused on the “polycentric” structure of each urban area, defined with respect to the number of employment centers within the area that exceed a specified level of employment density. The results show that the more polycentric an urban area is (i.e. the more employment centers it has), the higher the GHG emissions, all else equal. The authors explain that this may be because transit service in areas with multiple employment centers is likely to be of lower quality than in areas with few high-density employment centers. They conclude that increasing employment density near the central-business district (i.e. the primary employment center) can help to reduce GHG emissions from transportation. Co-benefits include reductions in energy consumption and GHG emissions for household uses.

Cervero and Murakami (2010) also used SEM to analyze the relationships between the built environment and VMT per capita, along with the associated GHG emissions, using data from 370 urbanized areas in the United States. After controlling for the impact of several additional land use and sociodemographic variables, the study found no statistically significant direct effects of employment density on VMT per capita. Instead, employment density influenced VMT indirectly through other variables associated with employment density. The strongest indirect effect of employment density was through population density and the geographic size of the urbanized area. First, the results suggest that higher employment density leads to higher population density and a larger urbanized area through the process of jobs attracting workers and thus households. Second, they suggest that higher population density leads to lower VMT, while a larger urbanized area leads to higher VMT. The net effect, after accounting for these off-setting effects, is a modest reduction in VMT per capita.

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