Built environment and travel behavior: Validation and application of a continuous-treatment propensity score stratification method

Abstract

This article discusses the validation and implementation of a propensity score approach with continuous treatments to test the existence of a causal relationship between the built environment and travel behavior using cross-sectional data. The implemented methodology differs from previous applications in the planning literature in that it relaxes the binary treatment assumption which polarizes the built environment into two extremes (e.g. urban vs suburban). The effectiveness of the proposed methodology in reducing bias was validated via Monte Carlo simulation using several data generating processes. Model results suggest that an increase in urbanization level –as measured by a newly-developed composite index of urbanization– has a negative effect on home-based maintenance car trip frequencies, and conversely, a positive effect on home-based maintenance non-motorized trip frequencies. Results estimates suggest the existence of a causal mode substitution mechanism between car and non-motorized modes given increases in the urbanization level at residential location, thus providing some empirical support to the arguments put forth by compact city advocates.

Keywords: *Travel behavior, Built Environment, Residential Self-selection, Causal Relationship, Propensity Score stratification, Monte Carlo Simulation.*

1. Introduction

Against the backdrop of urban sprawl and suburbanization, worsening traffic conditions and declining city centers, recent years have seen a paradigm shift in the conceptualization of what constitutes good urban development. Be it New Urbanism or Smart Growth in the United States, or Compact Cities in the EU and Japan, one of the main premises behind these new paradigms is that mixed-use, high density developments can significantly reduce automobile dependency and promote the use of alternative modes such as transit, bicycles or walking, thus resulting in more accessible, livable and inclusive neighborhoods and cities.

The underlying assumption behind this premise is that there exists a non-spurious, causal mechanism behind the built environment-travel behavior connection. Therefore, the main objective of this article is to test the existence or not of this causal mechanism. More specifically, this study seeks to answer the following research questions:

- Does the built environment, as measured by urbanization level at one's residential location, has a causal effect on maintenance trip frequencies by mode? If so, what is the nature of this effect?
- For maintenance trips, does a mode substitution effect exists between car and non-motorized modes given changes in the urbanization level at one's residential location?

In particular, given the scarce nature of panel data, this study focuses on establishing causality using more widely available cross-sectional data. To do so, a propensity score approach is implemented using a continuous treatment variable as proposed by (Author, 2014). This approach overcomes the main limitation of the existing binary approach as it takes into consideration the variability in the urbanization level of cities instead of arbitrarily polarizing the built environment into urban or suburban. This variability in urbanization is captured by a proposed continuous urbanization level index that serves as the treatment to be allocated. The estimation method allows for mitigation of the pervasive modifiable areal unit problem (MAUP). Furthermore, the performance of the continuous treatment propensity score method is validated through Monte-Carlo simulation.

The rest of the paper is structured as follows. Section 2 provides an overview of existing findings in the residential self-selection literature. Section 3 elaborates on the methodological aspects of this article including an overview of the propensity score approach (3.1), the generalization to continuous treatments (3.2), methodological comparison through Monte Carlo simulation (3.3), and the continuous treatment estimation (3.4). Section 4 details the general characteristics of the data used to test the study hypotheses, while Section 5 summarizes the modeling results. Finally, Section 6 wraps up the main conclusions of the article, its policy implications and limitations.

2. Literature review

A considerable number of studies have addressed the self-selection problem, and since the literature has been widely documented elsewhere (see Cao et al. (2009a), Author et al. (2015)), only a brief outlook is provided here, specifically focusing on studies analyzing trip/tour frequencies, unless otherwise stated.

From a cross-sectional approach, self-selection bias can be thought of as a kind of omitted variable bias. Consequently, this bias can be mitigated by including in the deterministic component of the model equation the variables associated with residential location, such as preferences and attitudes, as well as other socio-demographics. This approach is referred to by Mokhtarian & Cao (2008) as the statistical control approach. After accounting for attitudes and preferences, Kitamura et al. (1997) found that these factors explained a higher proportion of observed trip frequencies, and controlling for them reduced the magnitude of the land use effect. It is important to note; however, that attitudes and preferences do not render the built environment effect insignificant (Chatman, 2009). Using a similar strategy, strong effects have been observed particularly for non-motorized (NMM) trips, suggesting the existence of a mode substitution mechanism with private vehicles (Cao, et al., 2006; 2009b; Naess, 2009). The statistical control approach; however, is limited by the uncertainty of the effectiveness of the covariates used, especially in the case of attitudes, where there is no overarching theory guiding the definition and measurement of attitudes (Bohte, et al., 2009).

Khattak and Rodriguez (2005) found via an instrumental variable approach, that households in neo-traditional neighborhoods exhibit less car trips and shorter distances, even though overall trip frequencies are similar. Boarnet and Sarmiento (1998) used the percentage of buildings built between the 40s and 60s as an instrument for the built environment, and found no significant effects in most models and high sensitivity to model specification. On the other hand, using the same instrument, Vance & Hedel (2007) found evidence backing the existence of a casual mechanism between urban form and car use, and robustness to alternative model specifications. In spite of all, finding a proper instrument can be a difficult task.

From a quasi-longitudinal approach, changes in perception of accessibility have been associated with driving and walking level changes (Handy, et al., 2005; Handy, et al., 2006). SEM studies have also found evidence of mode substitution with higher level of car use and lower levels of transit use associated with suburban relocation (Scheiner & Holz-Rau, 2013), and reduced driving associated with relocation to neo-traditional neighborhoods (Cao, et al., 2007). The main limitation of this approach; however, is the risk of forgetting past behaviors, and the impossibility of measuring attitudes in the past (Cao, et al., 2007).

Finally, from a longitudinal approach, using first-differenced OLS regressions Krizek (2003) found that as neighborhood accessibility increases, number of household tours increase, yet driven distances decrease. Author et al. (2014b) found via a fixed effect model, evidence of substitution effect between nearby activities reached by non-motorized modes and faraway activities reached by car, given accessibility level changes at home location. Although ideal due to its proximity to an experimental situation, true panel data studies in the literature are rather few in number due mostly to data collection difficulties.

Propensity score applications in the planning literature

Although not extensively, several studies in the transport literature have implemented propensity score methodologies as a way to address the residential self-selection problem. In a non-randomized treatment assignment context, its attractiveness derives from the potential to remove bias stemming from a perhaps large set of observed covariates $\mathbf{X}_i$ using a single scalar function (Rosenbaum & Rubin, 1983).

Empirical findings suggest that even after controlling for residential self-selection, positive relations exist between vehicle kilometers driven and distance from the city center (Cao, et al., 2010), and between higher levels of business diversity and four-way intersections with more walking (Boer, et al., 2007). In addition individuals living in neo-traditional neighborhoods were found to walk more than those living in suburban areas (Cao, 2010).

Although these studies highlight the potential of the propensity score approach to mitigate selection bias, most studies polarized the built environment to a binary treatment (usually urban vs. suburban), ignoring the inherent variability in terms of how “urban” or how “suburban” a neighborhood is. In that sense, the continuous approach discussed in this article allows for the estimation of the average treatment effect by taking into consideration the full spectrum of variability in the urbanization level across a city, doing without the need to arbitrarily define what “suburban” or “urban” means.

3. Methodology

3.1. Propensity score function and treatment estimators: The binary treatment case

Rosenbaum and Rubin (1983) defined the propensity score function as the conditional probability of treatment given observed covariates. The theoretical basis supporting the propensity score are discussed in detail in Rosenbaum and Rubin, but are briefly summarized here in order to provide a general understanding of the concept at hand.

- *The propensity score as a balancing score*: Given a binary treatment z, as a function of observed covariates the propensity score will balance $\mathbf{X_i}$, so that conditional on the propensity score function $\mathrm{P}(\mathbf{X_i}) = \mathrm{P}(\mathrm{z_i}|\mathbf{X_i})$, the distribution of $\mathbf{X_i}$ is the same for treated and untreated groups. In other words, conditional on $\mathrm{P}(\mathbf{X_i})$, $\mathbf{X_i}$ and z are independent

1) $\Pr\{\mathrm{z_i}|\mathbf{X_i}, \mathrm{P}(\mathbf{X_i})\} = \Pr\{\mathrm{z_i}|\mathrm{P}(\mathbf{X_i})\}$

- *The strong ignorability assumption:* Given equation (1), strong ignorability of treatment implies that outcomes (Y_{0i},Y_{1i}) are independent from treatment assignment given $\mathrm{P}(\mathbf{X_i})$. In addition, every unit has a chance to receive either treatment state

2) $\mathrm{P}\{(Y_{0i}, \mathrm{Y}_{1\mathrm{i}})|\mathrm{z}_\mathrm{i}, \mathrm{P}(\mathbf{X}_\mathbf{i})\} = \mathrm{P}\{(Y_{0i}, \mathrm{Y}_{1\mathrm{i}})|\mathrm{P}(\mathbf{X}_\mathbf{i})\}\,; 0 < \mathrm{P}(\mathrm{z}_\mathrm{i} = 1|\mathrm{P}(\mathbf{X}_\mathbf{i}) < 1$

Rosenbaum and Rubin (1983) note that in a randomized trial the propensity score is a known function defined by the randomization mechanism. In a nonrandomized case; however, this function is not known but can be estimated from observed data, using limited dependent variable models such as the logit model in the case of discrete choices. Care should be taken to include as much relevant covariates as possible in the specification function.

Given that the two conditions above hold, Rosenbaum & Rubin (1983) show that at any value of the balancing score, the difference between the treatment and control means is an unbiased estimate of the average treatment effect at the value of the balancing score; as such, unbiased estimates of treatment effects can be estimated via several estimators. To do so, several approaches have been proposed, of which the most common are matching (Heckman, et al., 1998), weighting (Horvitz & Thompson, 1952; Imbens & Wooldridge, 2008), and stratification (Rosenbaum & Rubin, 1984), of which the latter is of most concern to this study, as it can be easily adapted to continuous treatment.

The stratification approach consists on sub-classifying the sample on J number of strata based on the propensity score where the ATE can be estimated as

3) $\mathrm{ATE}_{\mathrm{stratification}} = \sum_{j=1}^{J}\left(\bar{Y}_{j1} - \bar{Y}_{j0}\right) \cdot W_j$

where $\bar{Y}_{j1}$ is the mean outcome in class j when treated, $\bar{Y}_{j0}$ the mean outcome in class j when untreated, and W_j is the relative weight of strata j estimated as n_j/N. Rosenbaum and Rubin (1984) showed that a 5 strata sub-classification of the propensity score might reduce over 90% of bias due to observed covariates. Imbens & Wooldridge (2008) point out; however, that although five strata have been commonly used empirically, depending on sample size and the joint distribution of the data, fewer or more strata might results in lower mean square error.

3.2. Generalizing the propensity score to continuous treatments

A generalization of the propensity score method was proposed by Imai and van Dyk (2004) to allow for arbitrary treatment regimes T_i^A. Following Imai and van Dyk, the distribution of a continuous treatment T_i^A given a vector of covariates $\mathbf{X}_i$, is modeled as $\mathrm{T_i^A}|\mathbf{X_i} \sim \mathrm{N}(\mathbf{X_i^T}\boldsymbol{\beta}, \sigma^2)$. The propensity score function $\mathrm{P}(\mathbf{X_i}) = \mathrm{Pr}\{\mathrm{T_i^A}|\, \theta_{\boldsymbol{\psi}}(\mathbf{X_i})\}$ is assumed Gaussian distributed, and parameterized by $\boldsymbol{\psi} = \left(\boldsymbol{\beta}, \sigma^2\right)$, so that $\theta_{\boldsymbol{\psi}}(\mathbf{X_i}) = \mathbf{X_i^T}\boldsymbol{\beta}$. This implies that the propensity score function is solely characterized by the scalar θ, and its estimator $\widehat{\theta}_{\boldsymbol{\psi}}(\mathbf{X_i}) = \mathbf{X_i^T}\widehat{\boldsymbol{\beta}}$, is uniquely characterized by the conditional mean function of the linear regression of the treatment variable $\mathrm{T_i^A} = \mathrm{t^P}$ and all covariates $\mathbf{X}_i$, where $\mathrm{t^P}$ is a potential treatment.

It can also be shown that for non-binary treatments, the propensity score is as a balancing score

4) $\mathrm{Pr}\{\mathrm{T_i^A}|\mathbf{X_i}\,, \mathrm{P}(\mathbf{X_i})\} = \mathrm{Pr}\{\mathrm{T_i^A}|\mathrm{P}(\mathbf{X_i})\}$

and that given $P(\mathbf{X}_i)$ the outcome distribution of a potential treatment t^P, $Y_i(t^P)$ is independent from treatment assignment

5) $Pr\{Y_i(t^P)|\, T_i^A, P(\boldsymbol{X_i})\} = Pr\{Y_i(t^P)|P(\boldsymbol{X_i})\}$

for any $\mathrm{t^P} \in \mathcal{T}$, where $\mathcal{T}$ is a set of potential treatment values. Thus, by averaging $\mathrm{Pr}\{\mathrm{Y_i}(\mathrm{t^P})|\mathrm{P}(\mathbf{X_i})\}$ over the distribution of $P(\mathbf{X}_i)$, the distribution of the outcome of interest can be obtained as

6) $\Pr\{Y_i(t^P)\} = \int \Pr\{\mathrm{Y_i(t^P)} | \mathrm{T_i^A = t^P},\ \theta\} \Pr(\theta) d\theta$.

This integration can then be approximated parametrically as $\Pr_{\boldsymbol{\phi}}\{\mathrm{Y_i(t^P)} | \mathrm{T_i^A = t^P}\}$ stratified by the propensity score θ, where **ϕ** parameterizes the distribution. Thus, the distribution of $Y_i(t^P)$ can be approximated as the weighted average of the within strata outcome distribution

7) $\Pr\{Y_i(t^P)\} \approx \sum_{j=1}^{J} \Pr_{\widehat{\phi_j}}\{\mathrm{Y_i(t^P)} | \mathrm{T_i^A = t^P}\} \cdot \mathrm{W_j}$

where $\widehat{\phi_j}$ is the within strata estimate of unknown parameter **ϕ** in strata *j,* and W_j is the relative weight of strata *j*. **ϕ** can then be estimated as

8) $\widehat{\boldsymbol{\phi}} = \sum_{j=1}^{J} \widehat{\phi_j} \{\mathrm{Y_i(t^P)} | \mathrm{T_i^A = t^P}, \mathbf{X_i}\} \cdot \mathrm{W_j}$

where covariates $\mathbf{X_i}$ are included to control for variability of θ within strata. The average treatment effect is then a function of $\widehat{\phi}$; in this case, the weighted treatment coefficient of the regression of the outcome variable $Y_i(t^P)$ on t^P and all covariates, where weights are given by the sample relative weight n_j/N. Variance for the weighted coefficients can be estimated as

9) $\sum_{j=1}^{J} W_j^2 \cdot Var(\hat{\beta}_j)$

where W_j is the weight of each strata j, where $\sum_{j=1}^{J} W_j = 1$.

3.3. Methodological comparison through simulation

The performance of the propensity score methodology is tested against the OLS full-covariate model (statistical control approach) through Monte Carlo simulation. Two set of simulations are estimated, corresponding to home-based maintenance trips by car and by non-motorized means. Although relevant covariates related to travel behavior and residential location are known to some extent, the true data generating process is unknown, in that sense, Following Rubin & Thomas (2000) and Imai and van Dyk (2004), exponential functions were used to specify two data generating processes (DGP), an additive model and a multiplicative model, with different levels of linearity. For the additive models, departing from Imai and van Dyk, the data generating process is of the form

10) $$\mathrm{Y_i} = \delta_i\, T_i^A + \mathrm{c}_1(\lambda) \sum_{k=1}^{K} \boldsymbol{\lambda}_k e^{m_k \boldsymbol{X}_{ik}}$$

while for the multiplicative models, the data generating process is of the form

11) $$\mathrm{Y_i} = \delta_i\, T_i^A + \mathrm{c}_2(\lambda) e^{\sum_{k=1}^{K} \lambda_k \boldsymbol{X}_{ik}}$$

where for the *i*th individual, Y_i is the simulated outcome (e.g. home-based maintenance trip frequencies by mode), δ_i is the treatment effect, T_i^A is the assigned treatment, and $\boldsymbol{\lambda_k}$ is a vector of zero-mean Gaussian distributed coefficients for a vector of covariates $\mathbf{X_i}$ of *k* dimensions. The variance of $\boldsymbol{\lambda_k}$ is then used to control the level of linearity of each model. The component *m* in the additive model is a set of independently distributed variables that take values of -1 or +1 with equal probability. Each simulation was run with 1000 replications. In these applications the constants $\mathrm{c}_1(\lambda)$ and $\mathrm{c}_2(\lambda)$ are fixed to 1.

The degree of linearity of each model is measured by the average R^2 value of the regression of each function on the set of covariates **X** based on a 1000 replications[1]. For each DGP, three levels of linearity are considered. A highly linear model with average $R^2 \approx .95$, a moderately linear model with average $R^2 \approx .85$, and a moderately non-linear model average $R^2 \approx .75$.

As in Rosenbaum & Rubin (1984) and Imai & van Dyk (2004), the simulations are conducted under the assumption that the true propensity score function in known.

[1] Covariates are fixed among all replications as the observed values in the dataset are used.

3.4. Defining the treatment of interest: A continuous index of urbanization

Urbanization level at the location of residence, measured as a continuous variable, was defined as the treatment variable of interest. In order to quantify urbanization level, a latent variable model was specified using confirmatory factor analysis (CFA). CFA not only allows for a complete specification of the nature of relation between the latent factor and its indicators, but also allows for the calculation of goodness of fit statistics to test how well the estimated solution reproduces the observed variances and covariances of the indicators (Brown, 2006).

3.4.1. The spatial analysis unit

A critical part of the analysis is the definition of the basic spatial unit. Particularly due to the modifiable areal unit problem (MAUP), a pervasive yet widely ignored problem in spatial analysis, stemming from the way spatial data is aggregated. This problem, as argued by Fotheringham & Wong (1991) might have unpredictable effects in multivariate analysis. Given that spatial zones in widely used datasets such as the national census are defined rather arbitrarily, how sensitive are estimated results to changes in terms of zoning and scale is thus a non-trivial problem. Empirical research; however, has shown that a regular aggregation scheme such as a rectangular tessellation tends to produce more tractable results than aggregation on census geographic units (Putman & Chung, 1989; Zhang & Kukadia, 2005). Accordingly, to address the zonal problem, instead of the existing political district divisions, a regular sampling scheme is implemented. A 300m wide hexagon (150m from the center to any vertex) tessellation was used to subdivide the city area in regular spatial units. Although more common in ecological modelling, a hexagonal grid was selected as it presents some advantages over the rectangular grid, such as a better match in Euclidian distance measurements, and greater clarity in visualization (Birch, et al., 2007).

Regarding the aggregation scale problem, as suggested by Jelisnki & Wu (1996) and Dark & Bram (2007) a sensitivity analysis was conducted in order to analyze how sensitive results are to variations in the scale of analysis. Therefore, in addition to the 300m wide hexagon, three additional scales were used for the sensitivity analysis; 100m, 600m and 1000m wide hexagons (Sensitivity analysis results not included here, but are available upon request to the authors).

3.4.2. Definition of the indicator variables

In urban economics, combination of factors such as resource and transport advantage, economies of scale, and preference for variety in consumption and production are commonly agreed to give way to the urban agglomerations (Fujita, 1989). A myriad of factors such as land use allocation, land rent prices and population density are usually defined as functions of distance from the city center (Alonso, 1964; Mills, 1967; Fujita, 1989), while more recently in urban planning and transportation studies, particular attention has been given to the issue of accessiblity, as determined by the spatial distribution of potential destinations, its attractiveness and their ease of reach (Handy & Niemeier, 1997; Handy & Clifton, 2001).

Guided by urban economics and planning theory, a monocentric city would thus exhibit at its center higher access to goods and services (both in term of supply and ease of access), higher land use intensity and higher land prices, decreasing as one moves away from the center. Put another way, the closer to the city center, the higher the urbanization level. As such, for the purposes of this analysis urbanization level is conceptualized as a latent construct that accounts for the observed spatial distribution of the city in terms of supply of goods and services , land use intensity, transport mobility and land prices. Indicators were selected based on the results of an exploratory factor analysis (EFA) conducted on a set of potential indicators theoretically associated with urbanization levels. In addition, the spatial data used for this analysis (with the exception of population density) has the advantage of being available in the form of point data, which allows for a flexible definition of the analysis unit in order to address the MAUP issue discussed earlier. The four indicators used were:

A. Commercial Kernel density: Using location data of commercial facilities extracted from the geo-referenced phonebook data provided by ZENRIN Co., Ltd (2011), a Kernel density of all non-industrial services was estimated via *ArcGIS*, as a measure of supply of goods and services. As defined by Silverman (1986), the multivariate Kernel estimator can be written as

12) $\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left\{\frac{1}{h}(\boldsymbol{x} - \boldsymbol{X}_i)\right\}$

where *n* is the sample size, *h* is the bandwidth or smoothing parameter, and *K* is a Kernel weighting function, defined for a bivariate variable **x** following Silverman (1986) as

13) $K(x) = \begin{cases} 3\pi^{-1}(1 - \boldsymbol{x}^{\mathsf{T}}\boldsymbol{x})^2 & if\ \boldsymbol{x}^{\mathsf{T}}\boldsymbol{x} < 1 \\ 0 & otherwise \end{cases}$

A symmetrical density function is drawn on each data point (each commercial facility) following the specified Kernel weighting function in equation (13) extending up to the defined bandwidth *h* at which point the weight becomes zero. The kernel density is thus the sum of these density values at each sampling point where the sampling mesh size was set at 50m x 50m.

Bandwidth *h* was defined rather arbitrarily at 500 meters. Nevertheless, estimated density values at bandwidths of 500 meters, 750 meters and 1,000 meters yielded high correlations, with all coefficients above 0.95. In that sense, since CFA aims at reproducing the observed variances and covariances of the data, the bandwidth specification is of little concern for the purposes of this analysis.

B. Population density: Population density was used as a measure of land use intensity. Since data from the 2005 national census was used (PASCO, 2005), at its finest resolution, the data is available only at the district level, as a result, it not possible to control for the zoning effect in the data.

C. Weekday transit frequency was used as a measure of transport mobility. Railway data was gathered from publicly available service timetables from each operator (Fukuoka City Transport Bureau, 2014; JR Kyushu, 2014; JR West, 2014; Nishi-Nippon Railroad Co., Ltd, 2014) while bus data was provided by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT, 2011a; MLIT, 2011b). Weekday transit frequencies for locations within 800 meters from train stations, and 300 meters from bus stops were calculated and added, resulting in a single transit accessibility index.

D. Land price: Land price data was provided by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT, 2013a; MLIT, 2013b) . Land prices were interpolated from 1,965 data points extracted from the combined datasets via *ArcGIS* using the nearest neighbor method.

4. Survey design and data characteristics

The main data source for this analysis was an online survey conducted in the city of Fukuoka, Japan. The survey was conducted in December 2013, through Macromill, Inc. a net research company with over 2.3 million monitors all over Japan. The survey aimed at gathering four major types of information: (i) individual and household attributes, (ii) mobility biography (which includes relocation history and main modes of transport during different life stages (see Axhausen (2008)), (iii) attitudes related to transport and residential location, and (iv) travel behavior. The data gathered corresponds to a large extent to relevant covariates largely cited in the residential self-selection literature as playing in a role in co-explaining residential location and/or travel behavior (see Cao et al. (2009a) for an extensive review on the issue).

The target population was adults living in Fukuoka City at the time of the survey, and the sampling method used was stratified random sampling, where the stratification criteria was household composition. At first, respondents were randomly sampled from the monitor list and subjected to a pre-survey in order to gather data on their household composition. Respondents were then selected to participate in the main survey depending on the strata sizes and expected response rates. The survey was pre-tested using a convenience sample of students and faculty in the Department of ○○ of the University of ○○.

Table 1 compares the population distribution to the sampling distribution. The single elder cohort was underrepresented in the sample by almost 7 percentage points; conversely, the single young cohort was over-represented the same amount.

Table 1. Individual and household sample characteristics

Household type	**Frequency**	**Sample percentage**	**Population percentage**
Single household	314	47.9%	47.7%
Of which: Young (age 20-64)	*302*	*46.0%*	*39.2%*
Of which: Elder (age 65 and over)	*12*	*1.8%*	*8.5%*
Couples only	101	15.4%	15.1%
Of which: Young (age 20-64)	*60*	*9.1%*	*8.7%*
Of which: Elder (age 65 and over)	*41*	*6.3%*	*6.5%*
Nuclear household (including single parent households)	201	30.6%	31.3%
Three generation household & others	40	6.1%	6.0%
Total	**656**	**100%**	**100%**

Population data source: 2010 population census of Japan

Given the complexity of the survey, a computer interface was considered the best medium given the possibility of automatically tailoring the survey to the respondent's answers as the survey progresses. Concerning the possibility of coverage error stemming from the exclusion of people with no access to the internet or not enough digital literacy to answer the questionnaire, internet penetration rate for Japan was estimated at 79.1% for 2011. Among the 13-49 years old cohort, penetration rate stood up at 90%, while for the 60-64, 65-69, and 70-79 cohorts, rates stood at 73%, 60% and 42% respectively (MIC, 2012). In terms of digital literacy, MIC (2012) also estimated that among internet users, users who use the internet for purchases or trade accounted for 60%, although a gap was observed between users under 49 years old and older users. In that sense, in spite of a high diffusion rate, for older cohorts there might exist some limitations in terms of sample representativeness.

4.1. General characteristics of covariates

General sample characteristics were compared against population characteristics taken mainly from the 2010 national census and the 2011 Private Income Statistical Survey (National Tax Agency, 2012) to check the representativeness of the sample. Due to space limitations, in addition to general socio-demographics, only covariates that made the final propensity score model (see Section 5.1.) are summarized in Table 2.

As is usual in online questionnaires, the average age in the sample is lower than the population sample suggesting a slight bias towards the young. Sample average household size is also larger, with a sample average of 2.21 against the population average of 2.01. Compared against the Private Income Statistical Survey for 2011 (National Tax Agency, 2012), In general the income distribution is rather similar to the national average distribution, although consistent with the web-survey literature (Couper, 2000), higher income households are slightly over-represented in samples while lower income cohorts are somewhat underrepresented.

In order to account for the effect of built environment characteristics at previous locations respondents were asked to indicate the address of the 3 places where they have spent most of their lives (besides their current location, which was asked separately). In addition, respondents were asked to state the life-course events, if any, motivating these relocations. The most frequently cited reasons for moving to the present location are employment-related reasons (19%) marriage (12%) and school-related reasons (10%).

In terms of car ownership, the sample mean is estimated at 0.7 vehicles per household against a mean population value of 0.98 per household, the largest difference among measured variables. On the other hand, the ratio of driving license holders stands at 89% against a population ratio of 62%, although this difference might be partly explained by the exclusion of the under-20-years-old cohort.

Regarding attitudes and habits, automobile use habit was measured using the Response Frequency Index (RFI) proposed by Verplanken et al. (1994) . Respondents were presented with 10 hypothetical trips and given six travel modes (Car, train, bicycle, walk, motorbike and other) to choose from.

Table 2. Individual and household sample characteristics

Variable name	Mean	Population mean	Std.Dev.
Household characteristics		*2010 census data*	
Household size	2.22	2.01	1.38
Number of children	0.46	-	0.82
Number of cars	0.70	0.98	0.67
Driver to car ratio	0.84	-	0.29
Number of workers	1.08	-	0.70
House is company/school lodge	0.03	-	-
Job located in city center	0.33	-	-
Household yearly income[1]		*NTA National average*	
Under JPY2,000,000	0.20	0.24	-
From JPY2,000,001 to JPY3,000,000	0.18	0.17	-
From JPY3,000,001 to JPY4,000,000	0.16	0.18	-
From JPY4,000,001 to JPY5,000,000	0.12	0.14	-
From JPY5,000,001 to JPY6,000,000	0.11	0.09	-
From JPY6,000,001 to JPY7,000,000	0.07	0.06	-
From JPY7,000,001 to JPY8,000,000	0.06	0.04	-
From JPY8,000,001 to JPY9,000,000	0.03	0.03	-
From JPY9,000,001 to JPY10,000,000	0.02	0.02	-
From JPY10,000,001 to JPY12,000,000	0.03	0.04	-
Over JPY12,000,000	0.02		-
Lifetime events motivating relocation			
Work (start, change)	0.19	-	-
School(enrollment, change)	0.12	-	-
Wedding	0.10	-	-
Empty nest	0.01	-	-
Job promotion	0.02	-	-
Individual characteristics		*2010 census data*	
Male	0.48	0.47	-
Age	43.43	48.64	13.39
Driver (Valid driver's license)	0.89	0.62	-
Worker (as primary occupation)	0.66	-	-
University degree holder	0.49	-	-
Attitudes and habits			
Attitude: Car lover	-0.02	-	0.99
Attitude: Urbanite	0.06	-	0.98
Car use Habit	4.18	-	3.37
Life ratio using transit as main travel mode	0.35	-	0.36
Log of weighted population density at previous locations	9.03	-	0.90

[1]JPY 1 = USD 0.091

Habit was then measured as the simple summation of all the times car mode was selected. In terms of attitudes, a three factor Principal Component Analysis (PCA) was used to estimate the factors that explain unobserved attitudes towards residential location and transport. Respondents were asked to rate on a five point Likert Scale the level of agreement with 30 statements regarding private vehicles, public transport, non-motorized modes and residential location. The questionnaire design was largely based on previous studies by Kitamura et al. (1997) and Cao et al. (2009b), adapted to the Japanese case, and pre-tested accordingly.

4.2. Outcome variable of interest

The outcome variables considered for this analysis were home-based maintenance trip frequencies by mode. Maintenance activities refer to those activities other than subsistence activities (work and school related activities) that need to be conducted in the course of daily life such as grocery shopping, visits to the doctor, going to the bank, and other personal business. Discretionary activities were excluded as discretionary activity generation might be more dependent on factors such as social network characteristics, which are not controlled for in the current dataset. Respondents were asked to state the number of trips (excluding the return trip) taken during the week before up to the survey day by purpose and mode (see Table 3).

Table 3. Summary of reported travel behavior characteristics of the sample

Variable name	Mean	Std. Dev.	Minimum	Maximum
Total home-based maintenance trips	4.358	3.616	0	50
Of which: Car trip	*1.321*	*1.955*	*0*	*11*
Of which: Transit trips	*0.295*	*0.894*	*0*	*10*
Of which: Non-motorized trips	*2.741*	*3.301*	*0*	*40*

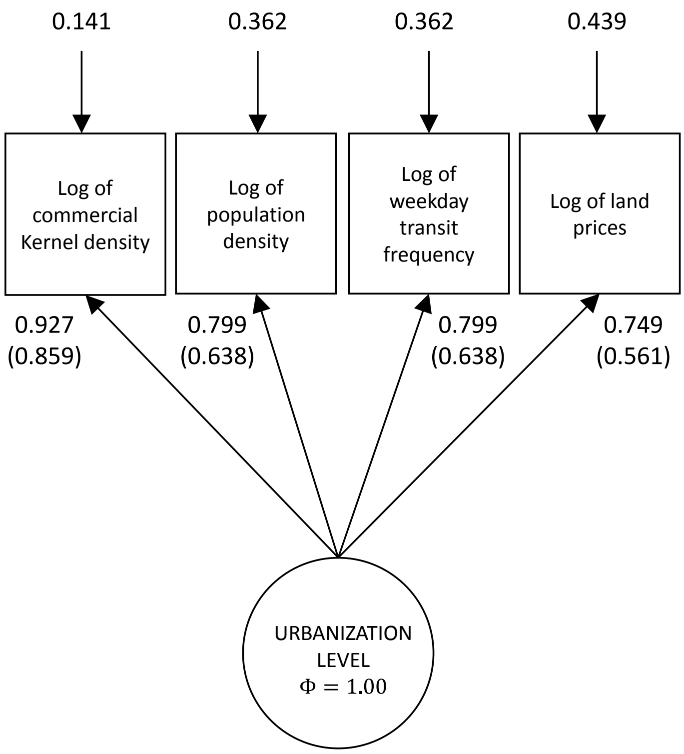
5. Model specification and results

5.1. Urbanization index model

Following the explanation provided in Section 3.4., The CFA model was estimated using MPLUS 6, developed by Muthen & Muthen (2010). Units were excluded from the analysis if (i) the population density at any given unit is equal to zero, or (ii) data for any of the indicator variables is not available for a given unit. This yielded an effective sample size of 18,485 cells out of the total 19,686 cells in which the study area was tessellated.

As a result of the multivariate non-normality condition of the indicator variables (i) all variables were introduced in their log form, and (ii) the robust maximum likelihood estimator was used. Although the issue of goodness of fit statistics remains still a hotly debated subject (Marsh, et al., 2004; Saris, et al., 2009; Heene, et al., 2011) Goodness of fit acceptable thresholds are guided by the values recommended by Hu & Bentler (1999) as follows: Standardized root mean square residual SRMR (≤0.08), comparative fit index CFI (≥0.95), Tucker-Lewis index TLI (≥0.95), and a root mean square error of approximation (RMSEA) cut-off value of ≤ 0.05.

With 2 degrees of freedom, the Chi-square statistic is significant at the 0.01 level. This might suggest that the model does not reproduce the observed variances and covariances of the indicators well enough; nevertheless, Chi-square is inflated by sample size, thus tending to routinely reject large sample size solutions (Brown, 2006). Other indices not sensitive to sample size, however, suggest an acceptable model fit. RMSEA is 0.037, with a confidence interval of 0.028 and 0.046 at its lower and upper boundaries respectively. CFI and TLI are 0.999 and 0.996 respectively, while the standardized root mean square residual (SRMR) is 0.005. The path diagram of the estimated latent variable is shown in Figure 1.



Chi-Square test of model fit (d.f.) 51.38 (2); p-value: 0.000; RMSEA (C.I. 90%) : 0.037 (0.028, 0.046)
Probability RMSEA ≤.05 : 0.994; CFI: 0.999; TLI: 0.996; SRMR: 0.005
Value in parenthesis is total explained variance by the factor.
All parameter estimates are significant at the p < 0.01 level.
Due to multivariate non-normality, estimator is Robust Maximum Likelihood.

Figure 1. Path diagram of "Urbanization Level" latent variable

Another criteria for evaluating the model was the modification indices, presented in Table 4. Modification indices reflect Chi-square changes given freely estimating the error covariances. In practice, modification indices above the 3.84 level suggest areas of strain in the model or potential improvements. However; since the indices reflect changes in Chi-square, they are also sensitive to large sample sizes. Fit-improving specification search guided by a sound theoretical reasoning is a widely accepted practice in the CFA field, and given the complexity of spatial dynamics, arguments can be put forth to support this approach. That is, the theory that other sources of covariation other than the urbanization latent factor exist among indicators is not at all unrealistic. However, in the absence of a well-established error theory to guide these specifications the current more parsimonious model was selected with error measures (unique variances) assumed random.

Table 4. CFA model modification indices

With statements	**Modification index**	**E.P.C.**	**STD E.P.C.**
Log of population density with log of Kernel density	9.714	-0.069	-0.068
Log of transit frequency with log of Kernel density	19.278	-0.105	-0.095
Log of transit frequency with log of population density	51.760	0.144	0.081
Log of land price with log of Kernel density	51.744	0.048	0.127
Log of land price with log of population density	19.230	-0.026	-0.044
Log of land price with log of transit frequency	9.714	-0.020	-0.031

E.P.C.: Expected parameter change; STD E.P.C.: Fully standardized expected parameter change
Only indices above 3.84 are reported

All estimated parameters were statistically significant at the 1% level. Factor loadings suggest that all indicators are strongly related with the latent factor urbanization level, especially the log of commercial density, whose total explained variance stands at 85.9%. Figure 2 illustrates the spatial distribution of the estimated urbanization level latent variable. Clearly, there is a marked mono-centricity in the spatial distribution of the city, with the highest levels of urbanization concentrated mainly around Chuo ward and spreading outwards.

A fixed-weight partial cross-validation test was conducted to validate the model beforehand. As proposed by MacCallum et al. (1994) the dataset was split into two mutually exclusive random samples; the first sample is used as to calibrate the model, while the second one is used to validate it. Results presented in this article use the full dataset.

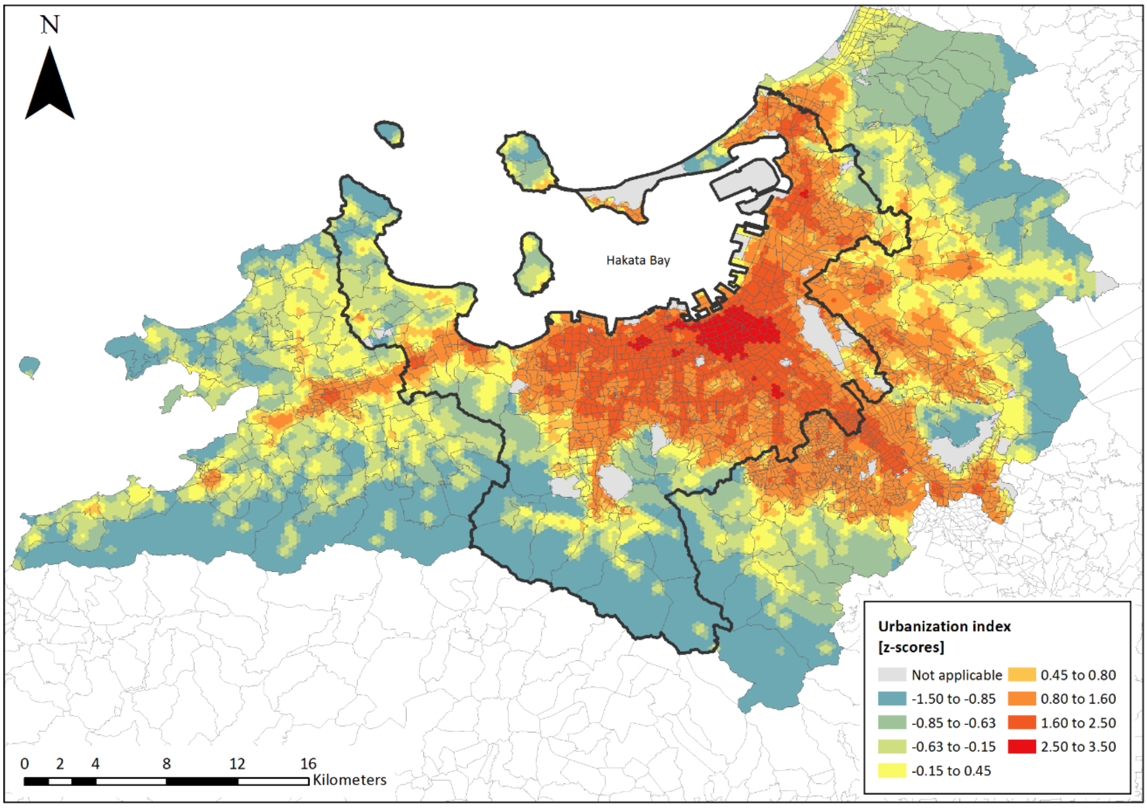


Figure 2. Urbanization level map of Fukuoka city

5.2. Estimating the propensity score function

As explained in Section 3.2., an estimate of the propensity score function $\hat{\theta}$ for the continuous treatment variable urbanization level is estimated through an OLS regression. Covariate selection was based both on findings from the literature as well as the theoretical considerations. Three types of variables are included in the regression function: household characteristics, lifetime events motivating the relocation and individual characteristics such as education level, habits and attitudes, which are assumed representative of those members involved in the residential location choice decision. Estimation results are presented in Table 5. R-squared of the final model was 0.25 suggesting an acceptable model fit. Note that the propensity score function is the same for both the simulations and the empirical analysis.

Table 5. Propensity Score OLS Estimation Results

N	491	S.E. of Regression	0.5331
Parameters	19	R-square	0.25
d.f.	472	Adj. R-square	0.22
RSS	134.14	F test (p-value)	8.66 (.0000)

Variable	***β***	**S.E.**	**t-Stat**
Constant	1.505	0.337	4.467
Household characteristics			
Household size	-0.087	0.039	-2.219
Number of children	0.110	0.053	2.079
Number of cars	-0.164	0.060	-2.726
Driver to car ratio	0.249	0.100	2.477
Number of workers	0.049	0.037	1.339
High Income	0.141	0.066	2.144
House is company/school lodge	-0.193	0.132	-1.465
Job located in city center	0.072	0.048	1.487
Lifetime events motivating relocation			
School(Start, change)	0.132	0.080	1.648
Wedding	-0.156	0.079	-1.981
Empty nest	0.707	0.327	2.161
Job promotion	-0.201	0.149	-1.354
Individual characteristics			
University degree holder	0.060	0.047	1.258
Attitudes and habits			
Attitude: Car lover	-0.035	0.025	-1.392
Attitude: Urbanite	0.059	0.025	2.368
Car use Habit	-0.034	0.012	-2.796
Life ratio using transit	0.103	0.068	1.503
Log of weighted population density at previous locations	0.049	0.033	1.517

It is important to note that as a prediction model, the object of interest of this regression is not the individual coefficients of each explanatory variable, but the scalar estimate $\widehat{\theta}$. Following the balancing score assumption described in equation (1), $\widehat{\theta}$ balances all the covariates thought to affect treatment allocation. This warrants the inclusion in the final model of variables that although theoretically significant might be rendered insignificant or exhibit the wrong sign due to multicollinearity.

To verify the balancedness of covariates given $\widehat{\theta}$, as suggested by Imai and Van Dyk (2004) each covariate was regressed against the original treatment variable. The same regressions were then run a second time but this time conditioning on $\widehat{\theta}$. OLS was used for continuous covariates while binary logit was used for dummy covariates. As Figure 3 illustrates, without controlling for $\widehat{\theta}$, most covariates are strongly correlated with the treatment, but once conditioned on the propensity score estimate, this correlation is considerably reduced, evident in the drop of the t-statistics for each covariate.

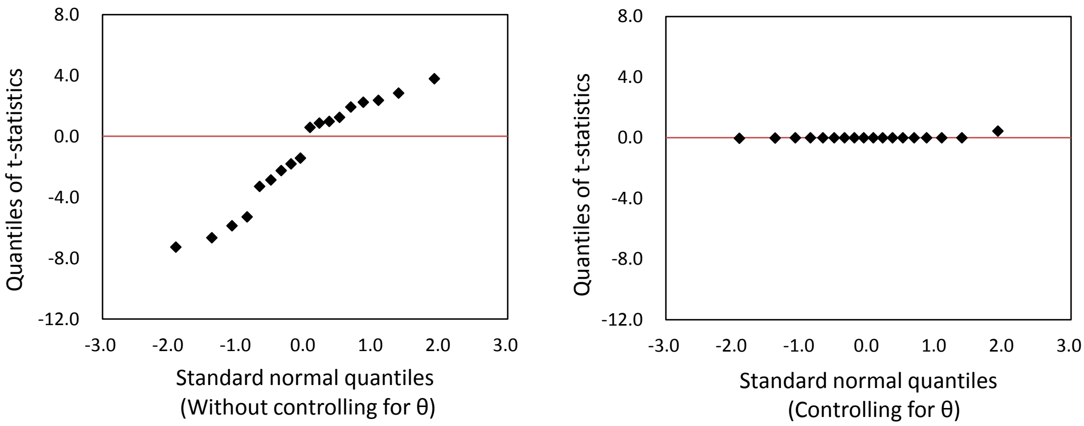


Figure 3. Standard Normal Quantile Plots of t-Statistics of covariates with and without controlling for the propensity score estimate

5.3. Measuring the performance of the propensity score stratification against OLS

As discussed in Section 3.3., for each of the 12 model specifications (3 additive models + 3 multiplicative models x 2 outcome variables), treatment effect is estimated using a full-covariate OLS, and propensity score stratification stratified on $\widehat{\theta}$ into roughly equal sub-classes *j,* where *j*= 3, 5 and 7 strata respectively. In addition all propensity score models are estimated with no covariates, and with the full set of covariates, totaling 72 models.

The performance of each model is compared against the full-covariate OLS estimates (statistical control approach), measured in terms of absolute bias where

(13) $\widehat{ABias} = \frac{1}{R}\sum_{r=1}^{R} \hat{\delta} - \delta$

and mean squared error where

14) $\widehat{MSE} = \frac{1}{R}\sum_{r=1}^{R}(\hat{\delta} - \delta)^2$

where $\hat{\delta}$ is the estimated treatment effect and R is the number of replications.

In terms of treatment effects, performance comparison is conducted first under the assumption of a fixed treatment effect that is constant to all individuals, and second, under the assumption of a variable treatment effect defined as a function of another variable. For the constant treatment effect, the estimated OLS values from full covariate models on the real dataset was used. In the variable treatment case the treatment parameter was defined as a function of car use habit, where for individual *i*

15) $\tilde{\delta}_{\mathrm{i}} = 10^{-1}(10 - \mathrm{H})\ \delta_{m}$

where H is the car use habit index as measured by the Response Frequency Index method, and δ_m is equivalent to the constant treatment parameter for mode m. Under this function, the treatment effect tends to zero as the car use habit increases. This is, however, an arbitrary function in order to illustrate the variable treatment case, but another function might have been used as well.

For the constant treatment case, simulated results are shown in Tables 6 and 7, for car trips and NMM trips respectively, while Tables 8 and 9 illustrate results for the variable treatment case. Results are given in percentage bias change (or MSE change) relative to the OLS estimates. Positive values indicate that the model underperforms the benchmark OLS model (bias increases relative to OLS), while negative values suggest that the model outperforms the benchmark model (bias decreases relative to OLS).

Compared to the OLS estimates, models stratified on the propensity score function reduced absolute bias up to 76% and mean squared error up to 94%, with full-covariates 5-strata and 7-strata models performing the best. Although in a very few cases the no-covariates stratified models outperformed all other models, more than 50% of these models underperformed the benchmark models, which supports the inclusion of all covariates in the estimation, a point that has also been noted by Imai and van Dyk (2004). In general, the simulation results suggest that propensity score stratification is indeed successful in reducing estimation bias against the OLS.

Table 6. Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by car (Constant treatment)

	3 strata		**5 strata**		**7 strata**	
% Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	7.43%	-1.90%	-1.89%	**-52.34%**	-15.24%	-26.89%
Moderately linear	9.94%	-2.82%	0.42%	**-51.25%**	-13.63%	-27.67%
Moderately non-linear	6.08%	-2.12%	-3.12%	**-52.90%**	-16.03%	-27.09%
Multiplicative models						
Highly linear	90.73%	-20.54%	22.33%	**-41.93%**	2.09%	-34.58%
Moderately linear	54.19%	-11.06%	5.59%	**-40.21%**	-4.28%	-12.54%
Moderately non-linear	17.14%	-17.68%	6.65%	**-28.08%**	2.28%	-10.91%
%Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	36.36%	-5.17%	13.61%	**-73.88%**	-20.05%	-47.31%
Moderately linear	44.43%	-7.51%	20.41%	**-72.30%**	-15.76%	-48.76%
Moderately non-linear	33.26%	-5.13%	11.06%	**-74.36%**	-21.19%	-47.31%
Multiplicative models						
Highly linear	384.55%	-41.61%	131.18%	**-70.69%**	41.03%	-49.44%
Moderately linear	137.92%	-45.90%	9.11%	**-82.97%**	-4.41%	-45.50%
Moderately non-linear	19.32%	-49.49%	2.47%	**-62.45%**	-4.59%	-51.94%

N.C.: No covariates; A.C.: All Covariates

Table 7. Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by NMM (Constant treatment)

	3 strata		5 strata		7 strata	
% Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	91.45%	-20.17%	13.69%	**-45.48%**	-10.20%	-44.82%
Moderately linear	42.77%	-16.80%	3.80%	-31.81%	-7.11%	**-32.77%**
Moderately non-linear	41.74%	-3.95%	13.14%	**-26.27%**	4.21%	1.93%
Multiplicative models						
Highly linear	5.54%	-1.76%	-3.63%	**-53.11%**	-16.29%	-26.78%
Moderately linear	2.65%	-1.46%	-6.26%	**-54.25%**	-17.87%	-26.56%
Moderately non-linear	9.66%	-2.54%	0.13%	**-51.49%**	-13.93%	-27.41%
% Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	173.19%	-34.20%	23.96%	**-73.37%**	-23.26%	-70.55%
Moderately linear	69.67%	-42.41%	4.01%	**-72.85%**	-13.35%	-68.13%
Moderately non-linear	61.30%	-22.94%	12.58%	**-60.43%**	1.35%	-33.21%
Multiplicative models						
Highly linear	36.44%	-5.62%	13.71%	**-73.80%**	-19.76%	-47.59%
Moderately linear	28.86%	-4.73%	7.41%	**-75.11%**	-23.02%	-47.08%
Moderately non-linear	40.15%	-6.19%	16.79%	**-73.16%**	-18.09%	-47.94%

N.C.: No covariates; A.C.: All Covariates

Table 8. Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by car (Variable treatment)

	3 strata		5 strata		7 strata	
Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	71.56%	17.37%	-22.48%	-11.00%	**-76.12%**	-47.57%
Moderately linear	43.31%	5.39%	-5.28%	-30.05%	-34.15%	**-35.12%**
Moderately non-linear	13.46%	-0.57%	-3.98%	**-48.47%**	-19.91%	-28.47%
Multiplicative models						
Highly linear	83.80%	4.16%	-10.38%	-27.72%	-49.54%	**-50.47%**
Moderately linear	52.12%	-15.31%	-0.26%	**-42.93%**	-10.83%	-30.01%
Moderately non-linear	24.86%	-15.01%	7.74%	**-28.15%**	1.67%	-16.06%
Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	193.78%	37.61%	-39.72%	-20.98%	**-94.03%**	-72.42%
Moderately linear	87.20%	6.09%	1.98%	**-57.34%**	-38.92%	-55.69%
Moderately non-linear	36.40%	-4.15%	9.90%	**-73.25%**	-22.50%	-47.78%
Multiplicative models						
Highly linear	385.66%	-1.44%	6.43%	-51.12%	-61.59%	**-74.62%**
Moderately linear	128.22%	-40.64%	1.95%	**-83.00%**	-17.77%	-65.17%
Moderately non-linear	27.17%	-45.21%	1.31%	**-62.79%**	-9.19%	-57.75%

N.C.: No covariates; A.C.: All Covariates

Table 9. Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by NMM (Variable treatment)

	3 strata		5 strata		7 strata	
Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	71.74%	17.39%	-22.46%	-10.90%	**-76.19%**	-47.61%
Moderately linear	40.45%	4.83%	-6.05%	-31.68%	-32.52%	**-33.98%**
Moderately non-linear	12.27%	-1.04%	-3.37%	**-49.34%**	-18.75%	-28.26%
Multiplicative models						
Highly linear	121.29%	-15.90%	16.92%	-33.12%	-2.26%	**-45.30%**
Moderately linear	49.74%	-24.81%	12.46%	**-43.38%**	-0.72%	-39.99%
Moderately non-linear	55.90%	-22.06%	28.87%	**-32.75%**	17.65%	-17.53%
Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	194.43%	37.67%	-39.70%	-20.80%	**-94.08%**	-72.48%
Moderately linear	80.91%	6.03%	-0.14%	**-59.00%**	-39.30%	-54.36%
Moderately non-linear	39.71%	-4.94%	13.05%	**-72.74%**	-20.79%	-48.04%
Multiplicative models						
Highly linear	210.75%	-40.19%	16.72%	-71.60%	-24.21%	**-74.01%**
Moderately linear	152.05%	-41.89%	45.23%	**-72.62%**	18.82%	-61.61%
Moderately non-linear	209.94%	-40.94%	100.00%	**-64.68%**	80.73%	-14.71%

N.C.: No covariates; A.C.: All Covariates

5.4. Empirical application to home-based maintenance trips

Having demonstrated the bias reduction potential of the propensity score approach, the method is applied to the Fukuoka dataset. In addition, a multi-scale analysis is conducted, largely motivated by the modifiable areal unit problem discussed before. Although given the way the treatment variable was estimated, both the zoning and scale problems are to some extent controlled for. However, the optimal scale of analysis, that is, the actual spatial scale that households consider when evaluating residential location alternatives is in practice not known. Guo & Bhat (2007) addressed this issue in terms of residential location choice models by operationalizing several definitions of “neighborhoods”. In addition to the census tracts, Guo & Bhat analyzed radial neighborhoods and network band models given different radii, namely, 0.4 km, 1.6 km and 3.2 km from each residential location alternative. Since the improvement of the more complex network band neighborhood was rather marginal, for this study the simpler radial network operationalization is used.

As illustrated in Figure 4, the first scale of analysis (Scale 1) is the same scale at which the urbanization level index was estimated, that is, a 300m diameter hexagon. The second and third scales take the unweighted average of the urbanization level of all units within a 1500 meter and 3000 meter radii respectively. In addition to the radial neighborhood operationalization, a more conceptually appealing analysis scale is proposed. The fourth scale of analysis assigns a weight to surroundings areas as a function of distance from each unit centroid via a kernel density function as described in Section 4.2 so that closer locations are given more importance than more distant ones. Recall that the kernel density function is rather insensitive to bandwidth (radius) specification, making the radius specification irrelevant.

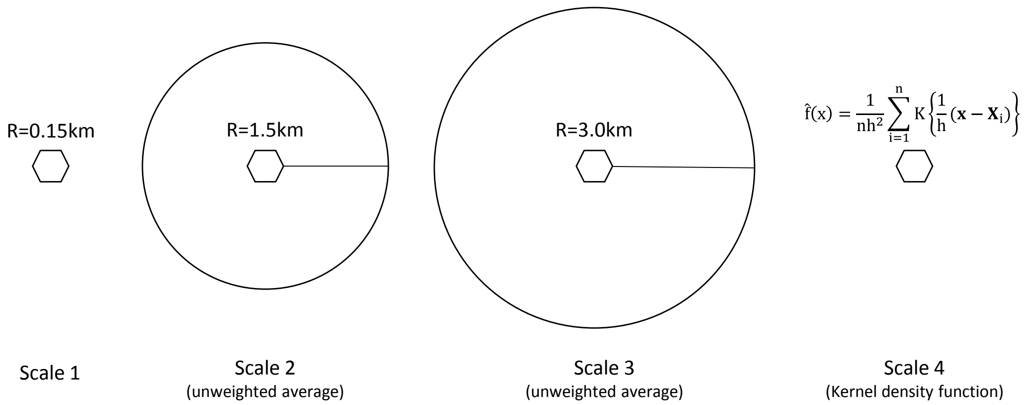


Figure 4. Diagram of scale definitions for multi-scale analysis

Tables 10 and 11 summarize the treatment effect estimates for full-covariate OLS against full-covariate 5-strata and 7-strata models at each spatial scale respectively. For all models, at any scale the direction of the effects is as hypothesized, negative for car trips and positive for non-motorized modes, thus supporting the idea of a mode substitution mechanism between car and non-motorized trips given changes in urbanization level.

Table 10. Multi-scale analysis of urbanization effect on home-based maintenance trips against 5 Strata estimates (Full-covariate models)

		Scale 1		Scale 2		Scale 3		Scale 4	
Model		**OLS**	**5 Strata**	**OLS**	**5 Strata**	**OLS**	**5 Strata**	**OLS**	**5 Strata**
Car trip frequency model	β	-0.201	-0.200	-0.145	-0.217	-0.127	-0.178	-0.131	-0.217
	t-Stat	-4.794	-3.381	-3.191	-5.020	-2.477	-4.106	-3.273	-5.110
	%Δ		-0.1%		50.0%		39.5%		65.7%
NMM trip frequency model	β	0.151	0.152	0.125	0.156	0.089	0.179	0.103	0.177
	t-Stat	2.595	2.604	1.924	2.710	1.215	3.230	1.746	3.025
	%Δ		0.4%		24.8%		101.0%		71.9%

Table 11. Multi-scale analysis of urbanization effect on home-based maintenance trips against 7 Strata estimates (Full-covariate models)

		Scale 1		Scale 2		Scale 3		Scale 4	
Model		**OLS**	**7 Strata**	**OLS**	**7 Strata**	**OLS**	**7 Strata**	**OLS**	**7 Strata**
Car trip frequency model	β	-0.201	-0.196	-0.145	-0.223	-0.127	-0.205	-0.131	-0.217
	t-Stat	-4.794	-4.326	-3.191	-4.592	-2.477	-4.220	-3.273	-4.381
	%Δ		-2.4%		54.1%		61.0%		65.8%
NMM trip frequency model	β	0.151	0.160	0.125	0.181	0.089	0.172	0.103	0.187
	t-Stat	2.595	2.545	1.924	2.989	1.215	3.023	1.746	3.245
	%Δ		5.9%		45.3%		92.4%		81.7%

At Scale 1, OLS and propensity score treatment effect estimates are rather similar, with differences ranging from 0.4% to 6% However, at different spatial scales, while the propensity score estimates are rather robust, the OLS estimates deteriorate quickly with difference in estimates up to 101%. Furthermore, in the NMM case, the t-statistics for the OLS estimates fall below the 5% threshold for all but the Scale 1 estimates, becoming insignificant at any significance level for the Scale 3 estimates. The multi-scale issue is certainly a non-trivial issue when considering the neighborhood operationalization problem discussed above.

6. Discussion and conclusion

This study validated through Monte Carlo simulation the propensity score approach as a tool to examine the connection between the built environment and travel behavior from a cross-sectional approach. It is shown that under the ignorability of treatment assumption, the causal effect of urbanization level on travel behavior can be estimated. By testing performance given different data generating processes, simulation results suggest that the propensity score approach can reduce absolute bias up to 76% and mean squared error up to 94% compared to OLS estimates. Empirically, the 5-strata and 7-strata full-covariate models performed the best.

As discussed in earlier, a continuous urbanization level treatment, as the one used here allows for a more precise understanding of the built environment effect on travel behavior at all levels of the urbanization spectrum without the need to arbitrarily draw a defining line between “urban” and “suburban” which binary treatment models might be highly sensitive to. Empirical analysis of data also suggested that the propensity score approach is more robust to changes in the scale of analysis, whereas the OLS performed rather poorly.

In terms of the propensity score function, the importance of the strong ignorability of treatment assumption cannot be over-emphasized. That is, the assumption that the distribution of treatment outcomes are independent from the distribution of treatment assignment given the propensity score is crucial to the unbiasedness of estimates. Nevertheless, in practice it is impossible to know how well the estimated function approximates the true population function. In order to estimate the propensity score function, relevant variables largely cited in the literature introduced in the model, hence, it is assumed at the estimated function is a good estimate of the true unknown function. However, the risk of misspecification is certainly non-trivial. In that sense, much care should be placed in estimating the propensity score function, as much of the validity of the analysis depends on it.

The main travel behavior dimension analyzed in this study relate to trip frequencies by mode. However, other relevant dimensions should be analyzed to strengthen the conclusions presented in this article. Certainly the propensity score approach presented here can be used to analyze continuous variables such as travel distance, or fuel consumption, provided reliable data is available.

In general, findings support the notion that the built environment has a significant effect on travel behavior, specifically, on trip frequency by mode, providing some empirical evidence to the claims of compact city advocates. Nevertheless, it is important to note that the issue at hand is more complex that just retrofitting or promoting a certain re-development model. In spite of the existence of a causal relation, residential location not only is a self-selecting process guided by household life-stage, lifestyle and preferences, but it's at the same time constrained by the supply and demand dynamics of the real estate market. In that sense, a mismatch between supply and demand might hamper efforts to promote compact city paradigms. Even for households that wish to move to the city center, rent costs might be prohibitively expensive, pushing households to more suburban areas where they can afford more space. In the case of Japanese cities, this problem is extenuated by lax urban control laws that allow development to expand even beyond the so called Urban Control Areas, thus promoting suburbanization, perhaps unintentionally.

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