Re-Examining the Built Environment-Travel Behavior Connection: A Case Study of Japanese Cities

都市の物的環境と交通行動の因果関係に関する研究

—日本の諸都市を事例として—

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The connection between the built environment and travel behavior has been the object of interest of a considerable number of studies in the past twenty years. As concepts such as Smart Growth, Compact Cities and New Urbanism permeate the sustainability discourse, the validity of the argument that high density, compact and mixed-use cities might reduce car use and promote the use of alternative modes hinges on the existence of a true causal mechanism between the built environment and travel behavior. This study uses data from several Japanese cities to test the existence of this causal relation using both panel and cross-sectional data. Findings suggest the existence of a causal mode substitution mechanism between car and non-motorized modes given increases in the urbanization level at residential location, providing some empirical support to the arguments put forth by Compact City advocates.

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, there seems to be a push towards more transit-connected, compact, and mixed-use cities, and neighborhoods that are more walkable, more bikeable, and more complete (Congress for the new urbanism, 2000; Kaido, 2001; Duany, et al., 2010).

One of the main premises behind the Compact City concept is the existence a non-spurious, causal mechanism behind the built environment-travel behavior connection. The validation of this causal relation is thus the principal object of interest of this dissertation. As such, the overarching research questions this study seeks to answer are:

- Is the effect of the built environment on travel behavior a causal effect?
- If so, what is the nature of this effect?

2. Literature review

2.1. Built environment, travel behavior and causality

In recent years, researchers have tried to validate the existence of a causal mechanism that would support the hypotheses put forth by high-density and mixed-use advocates. Although factors such as population density and land use mix have been consistently associated with lower levels of car use (Cervero & Kockelman, 1997) and car ownership (Sun, et al., 2012), findings are rather mixed. Although a great number of studies have established significant statistical associations between the built environment and travel behavior, establishing a causal relationship hinges on stronger conditions that are sometimes difficult to meet outside an ideal randomized experiment.

One particular threat that has drawn the recent attention of researchers in the planning field is the issue of residential self-selection, a form of selection bias. Using the jargon of program evaluation literature, in the built environment and travel context, the treatment of interest can be defined as the vector of built environment characteristics whose effect the analyst is interested in measuring (i.e. population density, land use mix, urbanization, etc.). Given that these characteristics are partly defined by residential location, and that households are free to choose their location, treatment assignment is not random. Residential self-selection bias thus occurs when treatment assignment (residential location) is defined in function of outcomes (the travel behavior of interest).

2.2. Addressing the self-selection problem

From a cross-sectional approach, self-selection bias can also 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. 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 that attitudes and preferences; however, 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; 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).

Using an instrumental variable approach, 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, 2007). The main limitation of this approach; however, is the risk of forgetting past behaviors.

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. 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. As such, the first analysis presented in this article consists of a panel data analysis.

3. Panel data analysis: empirical application on the Kashiwa no Ha Campus District

In order to contribute to the existing body of literature in an area where it is currently lacking, this section addresses the built environment and travel behavior relationship from a panel data perspective. Specifically, the object of interest is to understand how changes in the land use characteristics around home location affect activity frequency by mode. It is hypothesized that there exists a mode substitution mechanism between private vehicle and non-motorized modes given an increase in accessibility to any given activity around home location.

To test these hypotheses, data from a panel data survey conducted by The University of Tokyo between autumn 2007 and autumn 2008 on relocating households were used. The survey was conducted on households that purchased new apartments in the Park City Kashiwanoha Campus Project, located in the Kashiwanoha area of Kashiwa city, Chiba prefecture, at roughly 30 Kilometers from Tokyo (Figure 1). Information was gathered on household characteristics, individual travel behavior (activity frequency by mode) and lifestyle before and after moving.

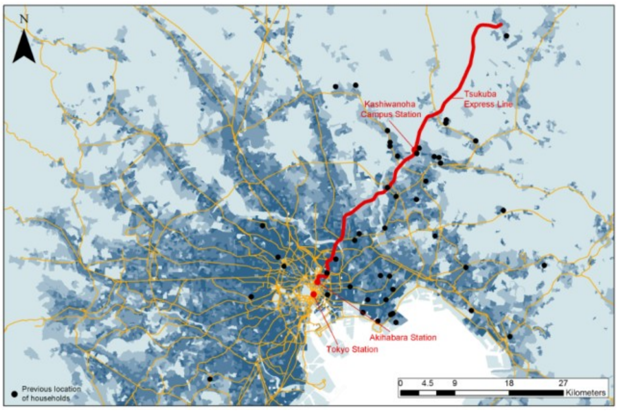

Figure 1. Location of the Park City Kashiwanoha Campus and Previous Location of Households (Image source: Troncoso Parady et al. (2014b))

A fixed effect model was used to estimate the effects of interest. The model is of the form

$$y_{it} = \alpha_i + \boldsymbol{\beta}\mathbf{x}_{it} + \boldsymbol{\gamma}\mathbf{z}_{it} + \varepsilon_{it} \tag{1}$$

where α is the unobserved individual fixed effect, **x** is a vector of time changing socio-demographics, **z** is a vector of time changing built environment features, and ε idiosyncratic error.

In the context of this analysis, let t_0 be the time period before moving, and t_1 be the time period after moving. Given model equations at t_1 and t_0 for the i_{th} individual respectively, by taking the deviation from mean at each time t, we then get a time demeaned equation for the i_{th} individual:

$$y_t - \bar{y} = \alpha - \bar{\alpha} + \boldsymbol{\beta}(\mathbf{x_t} - \bar{\mathbf{x}}) + \boldsymbol{\gamma}(\mathbf{z_t} - \bar{\mathbf{z}}) + \varepsilon_t - \bar{\varepsilon} \quad (2)$$

As shown in Tables 1-3, six models were estimated using different activity frequencies as dependent variables.

Table 1. Fixed effect model estimation results for overall activity frequency

Fixed Effect Model (robust)	Model 1: Log of yearly activity frequency by car		Model 2: Log of yearly activity frequency by NMM	
N	176		176	
No. of parameters	92		92	
Degrees of freedom	84		84	
SSR	175.97		168.99	
Standard error of e	1.45		1.42	
F test (prob) [df_r, df_{ur}] H_0: No fixed effect or fit in regression	3.26(0.000)	[91,84]	2.42(0.000)	[91,84]
F test (prob) [df_r, df_{ur}] H_0: No fit in the regression	7.05(0.000)	[4,171]	5.54(0.000)	[4,171]
F test (prob) [df_r, df_{ur}] H_0: No fixed effect	2.79(0.000)	[87,84]	2.133(0.000)	[87,84]
Log likelihood	-249.72		-242.44	
Restricted Log likelihood	-382.68		-359.50	
Chi-sq (prob) [df]	265.91(0.000)	[91]	226.69(0.000)	[91]
Variable	**β**	**t stat**	**β**	**t stat**
Change in distance to station (Km)	**0.246 (0.066)**	**3.723**	**-0.402 (0.137)**	**-2.919**
Car number reduction	-0.086 (0.273)	-0.313	0.327 (0.474)	0.690
Car number increase	**2.075 (0.488)**	**4.250**	-0.255 (0.390)	-0.654
Change in number of eating and non-grocery shopping facilities in a 0.5Km radius	- -	-	**0.022 (0.010)**	**2.090**
Change in overall number of facilities in a 1Km radius	**-0.010 (0.003)**	**-3.084**	- -	-
Classical model statistics test	**Log-L**	**R^2**	**Log-L**	**R^2**
1.Constant term only	-382.67	0.000	-359.50	0.000
2.Fixed effects only	-273.05	0.712	-272.84	0.626
3.Explanatory variables only	-369.23	0.142	-348.77	0.115
4.Explanatory variables and fixed effects	-249.72	0.779	-246.15	0.724

Results from the estimated models provide some evidence of the existence –after controlling for residential self-selection– of a causal relation between changes in the built environment and activity frequency, conditional on activity type and transport mode.

Changes in the built environment were found to exert a significant effect on shopping and eating-out frequency given location and travel mode. A mode substitution effect was observed in terms of changes in the number of facilities and activities by location and distance.

Changes in number of vehicles in the household had significant effects on several types of behavior, however, it is important to note that this effect was found to be asymmetric, that is, the effect of a one car increase in the household is not necessarily the same in terms of magnitude (with an opposite direction effect) or statistical significance as the effect of one car reduction, furthermore, this relationship might well be different given the type of activity.

There are some limitations to the present study that are worth discussing. Firstly, the effective sample size is rather small, which, particularly in the case of fixed effect models is important, considering the reduction in variability of the data as a result of exclusion of time invariant explanatory variables, resulting in larger standard errors, and lower R-square values.

Table 2. Fixed effect model estimation results for shopping frequency

Fixed Effect Model (robust)	Model 3: Log of yearly Car shopping frequency | Faraway		Model 4: Log of yearly NMM shopping frequency | Nearby	
N	192		184	
No. of parameters	101		97	
Df	91		86	
SSR	152.10		134.27	
Standard error of e	1.29		1.25	
F test (prob) [df_r, df_{ur}] H_0: No fixed effect or fit in regression	2.21(0.00)	[100,91]	1.81(0.02)	[97,86]
F test (prob) [df_r, df_{ur}] H_0: No fit in the regression	2.33(0.04)	[5,186]	2.51(0.02)	[6,177]
F test (prob) [df_r, df_{ur}] H_0: No fixed effect	2.13(0.00)	[95,91]	1.70(0.00)	[91,86]
Log likelihood	-250.07		-232.10	
Restricted Log likelihood	-368.38		-334.37	
Chi-sq (prob) [df]	236(0.0	[100]	204(0.00)	[97]
Variable	**β**	**t stat**	**β**	**t stat**
Change in distance to station (km)	**0.269 (0.094)**	**2.875**	-0.078 (0.085)	-0.937
Car number reduction	**-0.772 (0.425)**	**-1.816**	**0.829 (0.356)**	**2.327**
Car number increase	0.426 (0.439)	0.970	**-0.888 (0.453)**	**-1.963**
Change in distance to nearest grocery shop (km)	-0.105 (0.840)	-0.125	**-1.568 (0.639)**	**-2.453**
Change in number of grocery shops in a 0.5Km radius	- -	-	**-0.101 (0.027)**	**-3.811**
Change in number of non-grocery shops in a 0.5Km radius	- -	-	**0.037 (0.022)**	**1.713**
Change in number of grocery shops in a 1Km radius	-0.012 (0.008)	-1.461	- -	-
Classical model statistics	**Log-L**	**R^2**	**Log-L**	**R^2**
1.Constant term only	-	0.000	-334.37	0.000
2.Fixed effects only	-	0.667	-254.31	0.581
3.Explanatory variables only	-362.19	0.059	-326.85	0.078
4.Explanatory variables and fixed effects	-250.07	0.708	-232.09	0.671

Secondly, regarding external validity of results, it is important to note that given the nature of the study, inference might only be drawn for a specific socio-economic bracket and for specific changes in the built environment, such as those described earlier. Finally, attitudes are assumed constant in time, perhaps a strong assumption. A panel survey that measures attitudes in both periods would be ideal to rule out potential bias.

Table 3. Pooled OLS model estimation results for eating-out frequency

Pooled OLS (robust)	Model 5: Log of		Model 7: Log of	
N	190		184	
No. of parameters	5		5	
Df	185		179	
SSR	243.08		493.80	
Standard error of e	1.15		1.66	
R.sq.	0.13		0.16	
F test (prob) [df_r, df_{ur}]	6.76(0.000	[4,185	8.75(0.000	[4,179
Log likelihood	-293.00		-351.90	
Restricted Log likelihood	-305.96		-368.32	
Chi-sq (prob) [df]	25.90(0.00	[4]	32.84(0.00	[4]
Variable	**β**	**t stat**	**B**	**t stat**
Constant	**1.360** **(0.222)**	**6.133**	**1.684** **(0.327)**	**5.144**
Change in distance to station	-0.061 (0.086)	-0.709	**-0.386** **(0.138)**	**-2.804**
Car number reduction	-0.079 (0.334)	-0.233	-0.465 (0.488)	-0.952
Car number increase	-0.473 (0.361)	-1.310	0.3632 (0.650)	0.660
Change in number of eating and non-grocery shopping facilities in a 0.5Km radius	- -	-	**0.028** **(0.013)**	**2.250**
Change in number of eating and non-grocery shopping facilities in a 1Km radius	**-0.020** **(0.004)**	**-4.603**	- -	-

4. Cross-sectional analysis: A propensity score approach under continuous treatment regime.

Due to the difficulties associated with gathering true panel data, and the wide availability of cross-sectional data, the next section focuses on the causality issue from a cross-sectional approach. To do so, a propensity score approach is implemented.

The propensity score, defined as the conditional probability of treatment given observed covariates, was proposed by Rosenbaum and Rubin (1983) as a way to remove bias due to observed covariates. By acting as a balancing score in a non-randomized treatment (originally binary) assignment context, the propensity score makes inherently different groups comparable, the main advantage being the possibility of balancing a potentially large set of covariates **X** using one single scalar function. Rosenbaum and Rubin also showed that a 5 strata sub-classification of the propensity score might reduce over 90% of bias due to observed covariates.

In the planning literature several studies have highlighted the potential of the propensity score approach to mitigate selection bias (Boer, et al., 2007; Cao, 2010), however, 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, a continuous approach is discussed that 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.

This study follows the generalization of the propensity score method proposed by Imai and van Dyk (2004) to allow for arbitrary treatment regimes T^A. Following the proposed generalization approach, under a continuous treatment regime, the distribution of treatment T^A given a vector of covariates **X**, is modeled as $\mathrm{T^A}|\mathbf{X}\sim\mathrm{N}(\mathbf{X}^{\intercal}\boldsymbol{\beta},\sigma^2)$, where the propensity score function $\mathrm{P}(\mathbf{X}) = \mathrm{Pr}\{\mathrm{T^A}|\theta_{\boldsymbol{\psi}}(\mathbf{X})\}$ is Gaussian distributed and parameterized by $\boldsymbol{\psi} = (\boldsymbol{\beta},\sigma^2)$, and $\theta_{\boldsymbol{\psi}}(\mathbf{X}) = \mathbf{X}^{\intercal}\boldsymbol{\beta}$, thus the propensity score function is solely characterized by the scalar θ. In practice, $\widehat{\boldsymbol{\psi}}$ is estimated through a linear regression of the treatment variable $\mathrm{T^A} = \mathrm{t^P}$ and all covariates **X,** so that $\hat{\theta}_{\boldsymbol{\psi}}(\mathbf{X}) = \mathbf{X}^{\intercal}\widehat{\boldsymbol{\beta}}$, that is, the propensity score is uniquely characterized by the conditional mean function of the regression. Imai and Van Dyk, also demonstrated that even for non-binary treatments, the propensity score serves as a balancing score:

$$\mathrm{Pr}\{\mathrm{T^A}|\mathbf{X},\mathrm{P}(\mathbf{X})\} = \mathrm{Pr}\{\mathrm{T^A}|\mathrm{P}(\mathbf{X})\} \qquad (3)$$

and that the distribution of the outcome given a potential treatment t^P, $Y(t^P)$ is independent from treatment assignment given P(X):

$$\mathrm{Pr}\{\mathrm{Y}(\mathrm{t^P})|\,\mathrm{T^A},\mathrm{P}(\mathbf{X})\} = \mathrm{Pr}\{\mathrm{Y}(\mathrm{t^P})|\mathrm{P}(\mathbf{X})\} \qquad (4)$$

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

$$\mathrm{Pr}\{Y(t^P)\} = \int \mathrm{Pr}\{\mathrm{Y}(\mathrm{t^P})|\mathrm{T^A} = \mathrm{t^P},\theta\}\,\mathrm{Pr}(\theta)\mathrm{d}\theta. \qquad (5)$$

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

$$\mathrm{Pr}\{Y(t^P)\} \approx \textstyle\sum_{j=1}^{J} \mathrm{Pr}_{\widehat{\phi_j}}\{\mathrm{Y}(\mathrm{t^P})|\mathrm{T^A} = \mathrm{t^P}\}\cdot \mathrm{W_j} \qquad (6)$$

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

$$\widehat{\boldsymbol{\phi}} = \textstyle\sum_{j=1}^{J} \widehat{\phi_j}\,\{\mathrm{Y}(\mathrm{t^P})|\mathrm{T^A} = \mathrm{t^P},\mathbf{X}\}\cdot \mathrm{W_j} \qquad (7)$$

where covariates **X** 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 $Y(t^P)$ on t^P and all covariates, where weights are given by the sample relative weight n_j/N.

Imai and van Dyk (2004) verified through simulation and empirical analysis that stratification on the propensity score reduces bias of observed covariates by 16-95%, suggesting a superior performance over the direct non-stratified treatment estimation.

4.1. Methodological comparison through simulation

The performance of the propensity score methodology is tested against the OLS full-covariate model through Monte Carlo simulation. Two set of simulations are estimated, corresponding to home-based maintenance trips by car and by non-motorized means.

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

$$\mathrm{Y_i} = \delta_i\, T_i^A + \mathrm{c}_1(\lambda) \sum_{k=1}^{K} \boldsymbol{\lambda}_k e^{m_k \boldsymbol{X}_{ik}} \qquad (8)$$

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

$$\mathrm{Y_i} = \delta_i\, T_i^A + \mathrm{c}_2(\lambda) e^{\sum_{k=1}^{K} \lambda_k X_{ik}} \qquad (9)$$

where for the ith individual, $\mathrm{Y_i}$ is the simulated outcome (e.g. home-based maintenance trip frequencies by mode), δ_i is the treatment effect, $\mathrm{T_i}^A$ 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 $\mathbf{X}$ based on a 1000 replications. 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.

4.2. 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). A 300m wide hexagon (150m from the center to any vertex) tessellation was used to subdivide the city area in regular spatial units.

4.2.1. Defining the indicator variables

Guided by urban economics and planning theory, 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. Selected indicators were: (i) Commercial Kernel Density, (ii) Population Density, (iii) Transit Accessibility, and (iv) Land Prices.

4.3. Survey design and 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, (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. 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.

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.

4.4. Model Specification and results

4.4.1. Urbanization index model

Following the explanation provided in Section 3.4., A CFA model was estimated. 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. 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 illustrated in Figure 2.

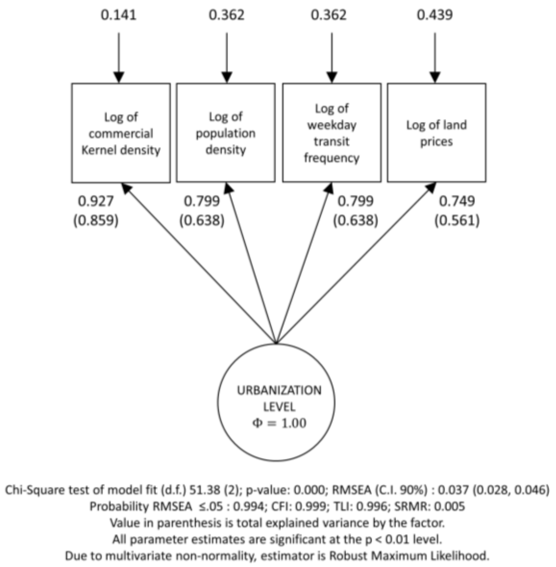

Figure 2. Path diagram of "Urbanization Level" latent variable

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 3 illustrates the spatial distribution of the estimated urbanization level latent variable.

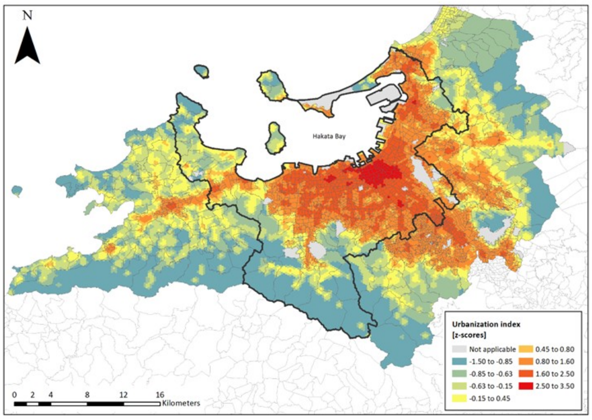

Figure 3. Urbanization level map of Fukuoka city

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

As discussed in Section 4.1., 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 $\hat{\theta}$ 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, measured in terms of absolute bias where

$$\widehat{ABias} = \frac{1}{R}\sum_{r=1}^{R}\hat{\delta} - \delta \tag{10}$$

and mean squared error where

$$\widehat{MSE} = \frac{1}{R}\sum_{r=1}^{R}(\hat{\delta} - \delta)^2 \tag{11}$$

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. In the variable treatment case the treatment parameter was defined as a function of car use habit, where for individual *i*

$$\tilde{\delta}_i = 10^{-1}(10 - H)\,\delta_m \tag{15}$$

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. This is, however, an arbitrary function in order to illustrate the variable treatment case, but another function might have been used as well.

Simulated results are shown in Table 7. 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).

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

Constant Treatment	Car Models		NMM Models	
	5 strata		5 strata	
% Change in ABIAS	N.C.	A.C.	**N.C.**	**A.C.**
Additive models				
Highly linear	-1.89%	-52.34%	13.69%	-26.89%
Moderately linear	0.42%	-51.25%	3.80%	-27.67%
Moderately non-linear	-3.12%	-52.90%	13.14%	-27.09%
Multiplicative models				
Highly linear	22.33%	-41.93%	-3.63%	-34.58%
Moderately linear	5.59%	-40.21%	-6.26%	-12.54%
Moderately non-linear	6.65%	-28.08%	0.13%	-10.91%
%Change in MSE	N.C.	A.C.	**N.C.**	**A.C.**
Additive models				
Highly linear	13.61%	-73.88%	23.96%	-47.31%
Moderately linear	20.41%	-72.30%	4.01%	-48.76%
Moderately non-linear	11.06%	-74.36%	12.58%	-47.31%
Multiplicative models				
Highly linear	131.18%	-70.69%	13.71%	-49.44%
Moderately linear	9.11%	-82.97%	7.41%	-45.50%
Moderately non-linear	2.47%	-62.45%	16.79%	-51.94%

Variable Treatment	Car Models		NMM Models	
	5 strata		5 strata	
% Change in ABIAS	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models				
Highly linear	-22.48%	-11.00%	-22.46%	-10.90%
Moderately linear	-5.28%	-30.05%	-6.05%	-31.68%
Moderately non-linear	-3.98%	-48.47%	-3.37%	-49.34%
Multiplicative models				
Highly linear	-10.38%	-27.72%	16.92%	-33.12%
Moderately linear	-0.26%	-42.93%	12.46%	-43.38%
Moderately non-linear	7.74%	-28.15%	28.87%	-32.75%
%Change in MSE	**N.C.**	**N.C.**	**N.C.**	**A.C.**
Additive models				
Highly linear	-39.72%	-20.98%	-39.70%	-20.80%
Moderately linear	1.98%	-57.34%	-0.14%	-59.00%
Moderately non-linear	9.90%	-73.25%	13.05%	-72.74%
Multiplicative models				
Highly linear	6.43%	-51.12%	16.72%	-71.60%
Moderately linear	1.95%	-83.00%	45.23%	-72.62%
Moderately non-linear	1.31%	-62.79%	100.0%	-64.68%

Compared to the OLS estimates, a 5-strata model reduces absolute bias up to 53%, and mean square error up to 83% suggesting a superior performance.

4.4.3. 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 since the optimal scale of analysis is actually unknown. 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. 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. Tables 10 summarizes the treatment effect estimates for full-covariate OLS against full-covariate 5-strata models at each spatial scale.

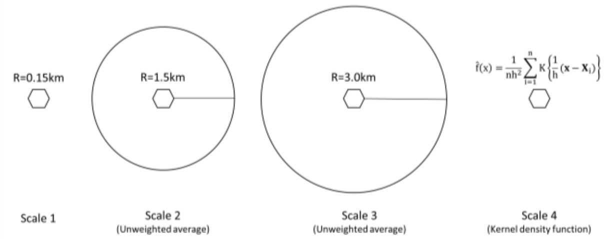

Figure 4. Diagram of scale definitions for multi-scale analysis

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

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

For all models, at any scale the direction of the effects is as hypothesized, negative for car trips and positive for non-motorized modes. 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.

5. Conclusions

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 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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