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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―

Giancarlos Troncoso Parady

トロンコソ　パラディ　ジアンカルロス

東京大学大学院工学系研究科都市工学専攻都市交通研究室

RATIONALE

- Paradigm shift in the conceptualization of what constitutes good urban development: **New Urbanism, Smart Growth, Compact cities**

- **In the case of Japan**(Kaido, 2001):
  - Ministry of Construction (Now MLIT) shifts from suburban development to existing urban areas in the late 1990's
  - Cities like Aomori, Kobe, Kanazawa, Fukui, Toyama incorporated Compact City ideas in their master plans

- **The premise:** mixed-use, high density developments can **significantly reduce automobile dependency and promote the use of alternative modes**. More accessible, livable and inclusive neighborhoods and cities.

RATIONALE

- **The underlying assumption:** The built environment exerts a strong enough influence on individuals and households to effectively change their travel behavior, that is, **A non-spurious, causal relation.**

Built environment → Travel Behavior

RESEARCH QUESTIONS

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

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SECTION 2

LITERATURE REVIEW

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CONDITIONS TO ESTABLISH A CAUSAL RELATION

(Mokhtarian and Cao,2008):

- Existence of a **statistically significant** association
- **Non-spuriousness** of this association
- **Time precedence** of the effect of interest

MORE GENERALLY:

(Meyer,1994):

Internal validity threats:

- Omitted variables
- Trends in outcomes
- Misspecified variances
- Mismeasurement
- Political economy
- **Simultaneity**
- **Selection**
- Attrition
- Omitted interaction

RESIDENTIAL SELF-SELECTION

THE SELF-SELECTION PROBLEM IN ITS SIMPLEST FORM

- Consider as the treatment T^A of interest a vector of built environment variables
- Consider as the (continuous) outcome variable $f_i(T^A)$, a measurement of the travel behavior of interest
- Consider a naïve hypothesis:

$$f_i(T^A) = \alpha + T^A\beta + \varepsilon$$

- The treatment of interest is a function of residential location, **a non-random process.**
- Residential self-selection bias stems from a **correlation between the treatment assignment and observed outcomes**. In other words a correlation with the error term.

STUDIES ADDRESSING THE SELF-SELECTION PROBLEM

Cross-sectional approaches (25)

- Statistical control (8)
- Instrumental variables (3)
- Sample selection and propensity score (6)
- Discrete choice joint modeling (5)
- Structural equation models (SEM) (3)

Quasi-longitudinal approaches (4)

- Same as above (4; including all approaches)

Longitudinal approaches (4)

- Pooled OLS (1)
- First differenced models and Fixed effect models (2*)
- Difference in differences models (1*)

*Not directly related to planning or transportation

GENERAL FINDINGS FROM THE LITERATURE [IN A NUTSHELL]

- In general there is a **rather well established statistical association** between built environment and travel behavior.
  - Higher population density & mixed land use with less car travel
  - Higher population density & mixed land use with more travel by alternative modes
  - Some studies also suggest the **effect of the built environment might not significant**

- The effect of the built environment differs given activity types.
  - **Strongest effects observed for non-work trips** (with the exception of leisure activities)

- Factors associated with **travel attitudes, personality and lifestyle** might mitigate self-selection. **Habits** might also play a key role in explaining behavior.

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SECTION 3

CROSS-SECTIONAL ANALYSIS AND THE CAUSALITY PROBLEM

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SECTION OBJECTIVES

① **Understand the conditions for establishing causality using cross-sectional data [and its limitations]**

② **Introduction of the propensity score as an approach to overcome these limitations [binary treatment case]**

③ **Introduction of a generalization of the propensity score To continuous treatments**

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① Understanding the conditions for establishing causality using cross-sectional data [and its limitations]

- To motivate the problem at hand, first consider a naïve hypothesis of the relationship between the built environment and travel behavior.

Built environment (z) → Travel Behavior (Y)

- **Further assume that the built environment treatment variable of interest is binary** (i.e. urban vs suburban), following Rubin (1977), we can define:

Average treatment effect

ATE →
$$E[y_{1i} - Y_{0i}] = E[Y_{1i}] - E[Y_{0i}]$$

Average treatment on treated

ATT →
$$E[Y_{1i} - Y_{0i}|z_i = 1] = E[Y_{1i}|z_i = 1] - E[Y_{0i}|z_i = 1]$$

$E[Y_0|z = 1]$ **however, is not observed. It's a COUNTERFACTUAL!**

Where

$$z = \begin{cases} 1 & \text{Treated (Urban)} \\ 0 & \text{Untreated (Suburban)} \end{cases}$$

Y_{1i} = Outcome when treated

Y_{0i} = Outcome when untreated

① Understanding the conditions for establishing causality using cross-sectional data [and its limitations]

- However, to the extent that the **treatment is truly randomly allocated,** treatment is independent from outcomes $(Y_{0i}, Y_{1i} \perp z_i)$ thus

This we CANNOT observe

$$E[Y_{0i}|z_i = 1] = E[Y_{0i}|z_i = 0]$$

This we can observe

so we can substitute and get

$$E[Y_{1i} - Y_{0i}|z_i = 1] = E[Y_{1i}|z_i = 1] - E[Y_{0i}|z_i = 0]$$

Where the Average Treatment Effect (ATE) equals the Average Treatment on Treated (ATT).

The problem with this naïve estimator that **a truly random experiment of residential location is virtually impossible.**

① Understanding the conditions for establishing causality using cross-sectional data [and its limitations]

- **In the absence of randomization the estimated coefficients are biased and inconsistent.** This can be easily seen by restating the ATT equations as

$$E[Y_{1i} - Y_{0i}|z_i = 1]$$

$$= E[Y_{1i}|z_i = 1] - E[Y_{0i}|z_i = 1] + (\mathbf{E[Y_{0i}|z_i = 1] - E[Y_{0i}|z_i = 0]})$$

Selection Bias

Under randomization $Y_{0i}, Y_{1i} \perp z_i$; Bias = 0

① Understanding the conditions for establishing causality using cross-sectional data [and its limitations]

- Consider now, under the **conditional independence assumption (CIA),** that the treatment of interest is independent from the observed outcomes given a set of covariates **X** $(\mathrm{Y_{0i}, Y_{1i}} \perp \mathrm{z_i} | \mathbf{X}_\mathrm{i})$.

- Angrist (1998) shows that by **matching** on all values of **X**, and by the law of iterated expectations, **in the case of discrete covariates**, the Average Treatment on Treated (ATT) can be estimated as:

$$E[Y_{1i} - Y_{0i}|z_i = 1] = E\{E[Y_{1i} - Y_{0i}|z_i = 1, \boldsymbol{X_i}]|z_i = 1\}$$

(By CIA) $$= E\{E[Y_{1i}|z_i = 1, \boldsymbol{X_i}] - E[Y_{0i}|z_i = 0, \boldsymbol{X_i}]|z_i = 1]\}$$

$$= \frac{\sum_x \beta_x P(z_i = 1|\boldsymbol{X_i} = x)P(\boldsymbol{X_i} = x)}{\sum_x P(z_i = 1|\boldsymbol{X_i} = x)P(\boldsymbol{X_i} = x)}$$

Where β_x = $E[Y_{1i}|z_i = 1, \boldsymbol{X} = x] - E[Y_{0i}|z_i = 0, \boldsymbol{X} = x\ ]$. That is, he difference of the mean between treated an untreated for any given value of x.

① Understanding the conditions for establishing causality using cross-sectional data [and its limitations]

- **Empirical evidence suggests that violations to the linearity condition might result in strong estimation bias in OLS case** (Imai & van Dyk, 2004). which might favor the use of matching and stratification approaches to estimate causal effects in the absence of randomization.

- **However, as the number of covariates increases, the number of sub-classes increases exponentially,** rendering many subclasses empty, or with either no control or treated units, making impossible to draw estimates for the whole population (Corchran, 1965; Rosenbaum & Rubin, 1984).

- To address that problem Rosenbaum and Rubin (1983) proposed **a scalar function that summarizes the information necessary to balance the covariate distribution**, this function is called the propensity score.

② Introduction of the propensity score as an approach to overcome these limitations **[binary treatment case]**

THE PROPENSITY SCORE APPROACH

- The propensity score, defined **as the conditional probability of treatment given observed covariates**, was proposed by Rosenbaum and Rubin (1984) as a way to remove bias due to observed covariates in binary treatments:

THEORETICAL BASIS:

Following Rosenbaum and Rubin (1983)

① **"The propensity score is a balancing score":** conditional on P($\mathbf{X}_i$), the distribution of $\mathbf{X}_i$ and z are independent

$$\Pr\{z_i|\mathbf{X}_i, P(\mathbf{X}_i)\} = \Pr\{z_i|P(\mathbf{X}_i)\}$$

The propensity score makes inherently different groups comparable

② **Introduction of the propensity score as an approach to overcome these limitations** **[binary treatment case]**

THE PROPENSITY SCORE APPROACH

② **"If treatment assignment is strongly ignorable given x, it is strongly ignorable given any balancing score"**
strong ignorability of treatment implies that outcomes (Y_{0i},Y_{1i}) are independent from treatment assignment given P($\mathbf{X}_i$). In addition, every unit has a chance to receive either treatment state

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

$$0 < \mathrm{P}(\mathrm{z}_\mathrm{i} = 1|\mathrm{P}(\mathbf{X}_\mathbf{i}) < 1$$

③ "At any value of a 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 if treatment assignment is strongly ignorable"**

THE PROPENSITY SCORE APPROACH

P(X) ESTIMATION

This function is not known but **can be estimated from observed data**, using limited dependent variable models such as the **logit model** or **probit model.**

ATE ESTIMATION

- **MATCHING**

$$\mathrm{ATE}_{\mathrm{matching}} = N_1^{-1} \sum_{i=1}^{N} \left\{ Y_{1i} - \sum_{j \in \{z=0\}} W_{N0N1}(i,j) Y_{0j} \right\}$$

Where $W_{N0N1}(i,j)$ is a weight function (several estimators exist)

- **WEIGHTING**

$$\mathrm{ATE}_{\mathrm{weighting}} = N^{-1} \sum_{i=1}^{N} \left[\frac{Y_i \cdot z_i}{P(\boldsymbol{X}_i)} - \frac{Y_i \cdot (1 - z_i)}{1 - P(\boldsymbol{X}_i)} \right]$$

- **STRATIFYING**

$$ATE_{stratification} = \sum_{j=1}^{J} (\bar{Y}_{j1} - \bar{Y}_{j0}) \cdot W_j$$

② **Introduction of the propensity score as an approach to overcome these limitations** **[binary treatment case]**

THE PROPENSITY SCORE APPROACH IN PLANNING STUDIES

- **Several studies in the transport literature have implemented propensity score** methodologies as a way to address the self-selection issue. :
  - *Boer et al(2007), Cao et al (2010), Cao (2010)*
- Nevertheless, **polarizing the built environment to a binary treatment** (usually urban vs. suburban) is a rather **strong assumption.**
- Ignores the spectrum of variability in terms of **how "urban" or how "suburban" a neighborhood might be .**
- **Binary approach is adequate in the case of neighborhood to neighborhood comparisons** as previous studies demonstrated but not practical for large scale analysis at the city level.

③ **Introduction of a generalization of the propensity score to continuous treatments**

GENERALIZING THE PROPENSITY SCORE TO CONTINUOUS TREATMENTS

- Following a propensity score generalization under continuous treatment regimes, proposed by Imai and Van Dyk (2004):

  - The distribution of an arbitrary treatment T^A given a vector of covariates **X**, is modeled as $\mathrm{T}^{\mathrm{A}}|\mathbf{X} \sim \mathrm{N}(\mathbf{X}^{\intercal}\boldsymbol{\beta}, \sigma^2)$

  - **The propensity score function is solely characterized by the scalar $\boldsymbol{\theta}_{\boldsymbol{\psi}}(\mathbf{X}) = \mathbf{X}^{\intercal}\boldsymbol{\beta}$ (The conditional mean function, estimated via OLS)**

  - The propensity score serves as a **balancing score:**

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

  - **Strong ignorability of treatment:**

$$Pr\{Y(t^P)|\, T^A, P(\boldsymbol{X})\} = Pr\{Y(t^P)|P(\boldsymbol{X})\}$$

GENERALIZING THE PROPENSITY SCORE TO CONTINUOUS TREATMENTS

- By averaging $\Pr\{Y(t^P)|P(\mathbf{X})\}$ over the distribution of P(**X**), the distribution of the outcome of interest can be obtained as

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

Thus, the distribution of $Y(t^P)$ can be approximated by **stratifying on the propensity score estimate $\hat{\theta}$**

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

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*

GENERALIZING THE PROPENSITY SCORE TO CONTINUOUS TREATMENTS

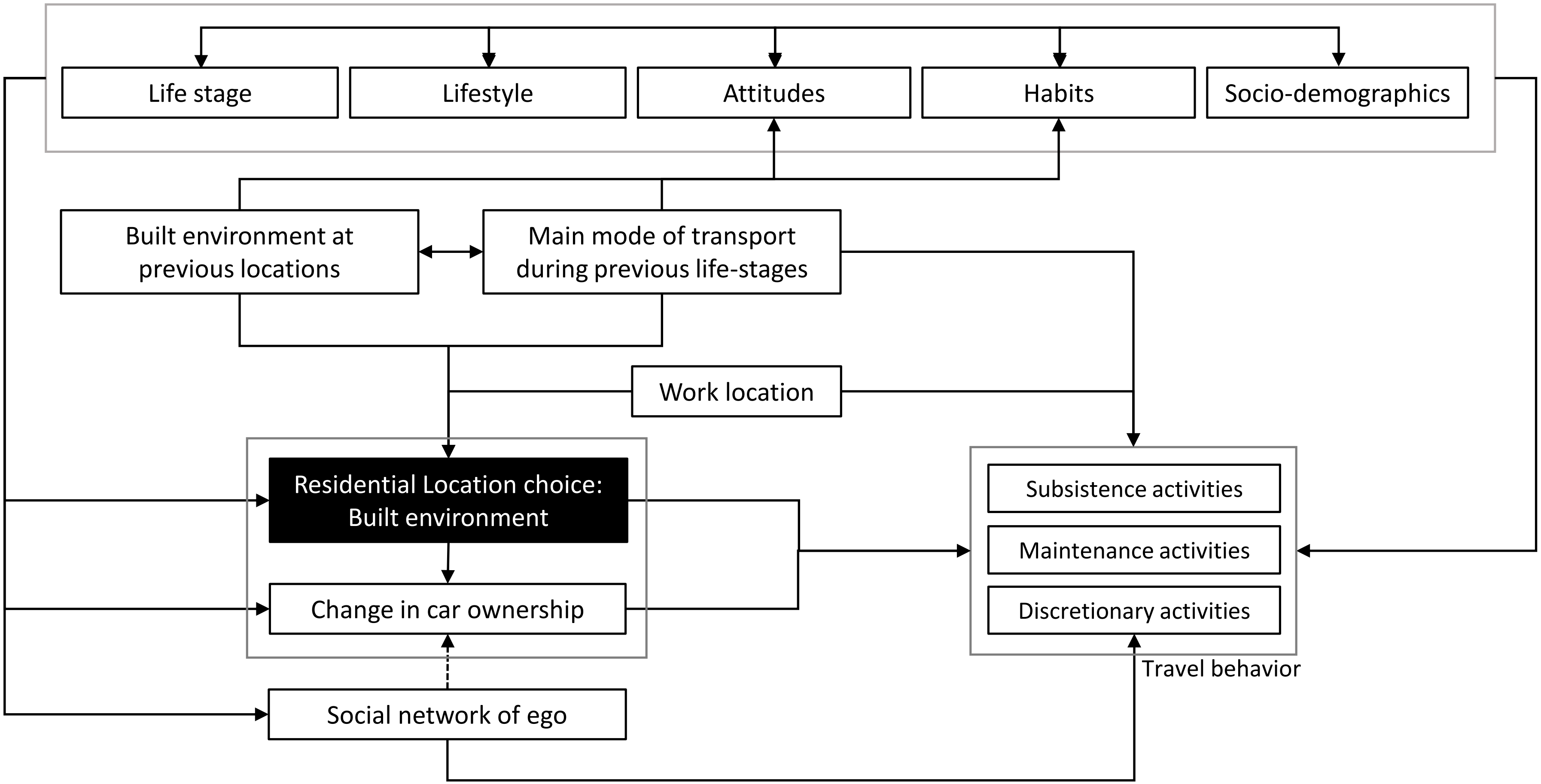
The object of interest (ATE) is thus:

$$\widehat{\boldsymbol{\Phi}} = \sum_{j=1}^{J} \widehat{\phi_j} \left\{ Y\left(t^P\right) \middle| T^A = t^P, \mathbf{X} \right\} \cdot W_j$$

Where $\widehat{\phi_j} \left\{ Y\left(t^P\right) \middle| T^A = t^P, \mathbf{X} \right\}$ is the within strata estimated treatment parameter

Covariates **X** are included to control for variability of θ within strata.

HYPOTHESIZED RELATION OF TREATMENT AND COVARIATES



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SECTION 4

TREATMENT VARIABLE ESTIMATION: A LATENT CONSTRUCT OF URBANIZATION

THE CASE OF FUKUOKA CITY

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ESTIMATING THE TREATMENT OF INTEREST

How to define the continuous treatment?

Urbanization level operationalized as a latent variable

Estimated via Confirmatory Factor Analysis

- Allows for calculation of **goodness of fit statistics**

Addressing the MAUP problem:

- Use of a **regular aggregation scheme** (300m diameter hexagon tessellation)
- **Sensitivity analysis** of scale of spatial unit

  Hexagon diameter: 100m, 300m*, 600m, and 1000m

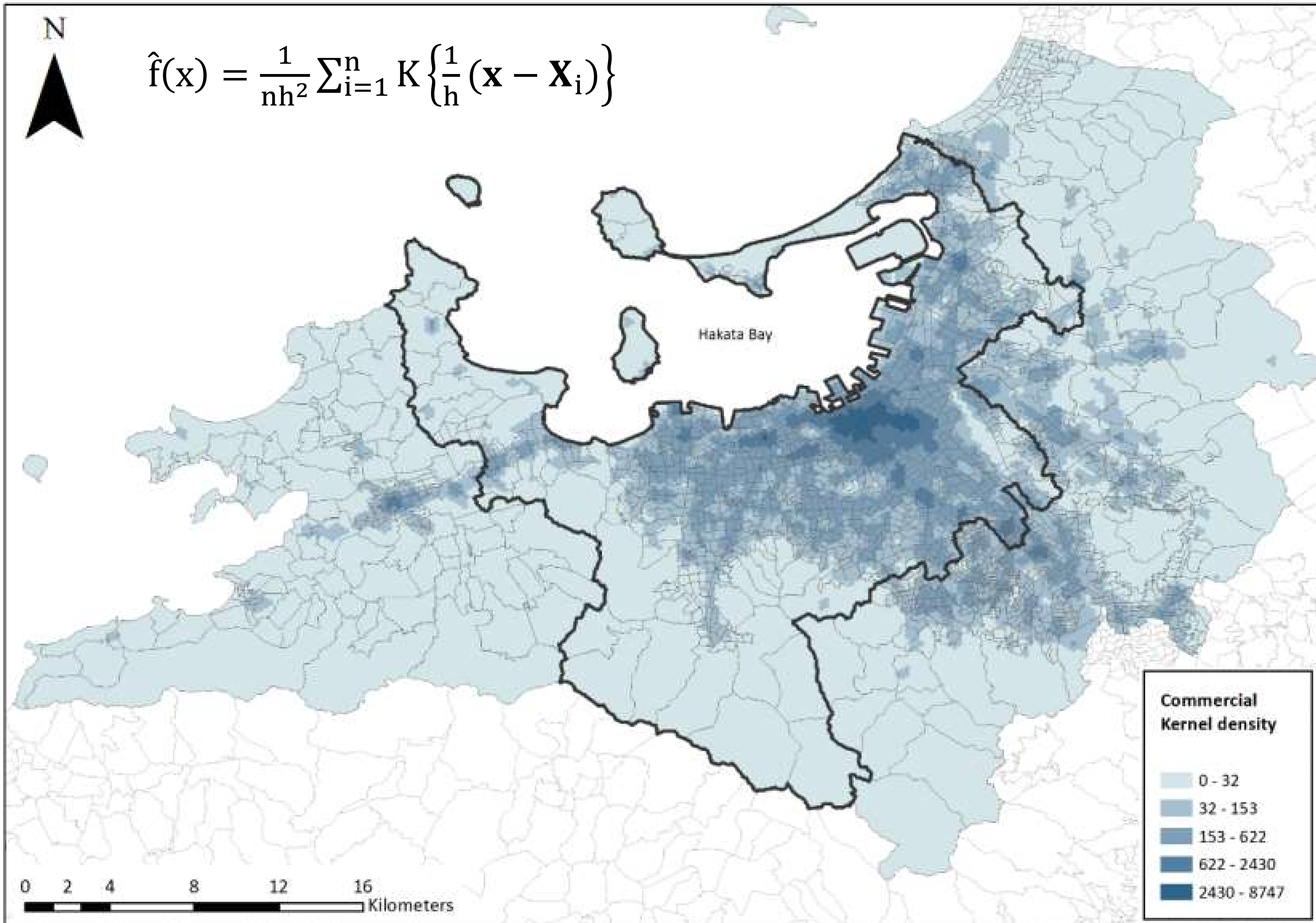
Definition of indicator variables

- 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.**

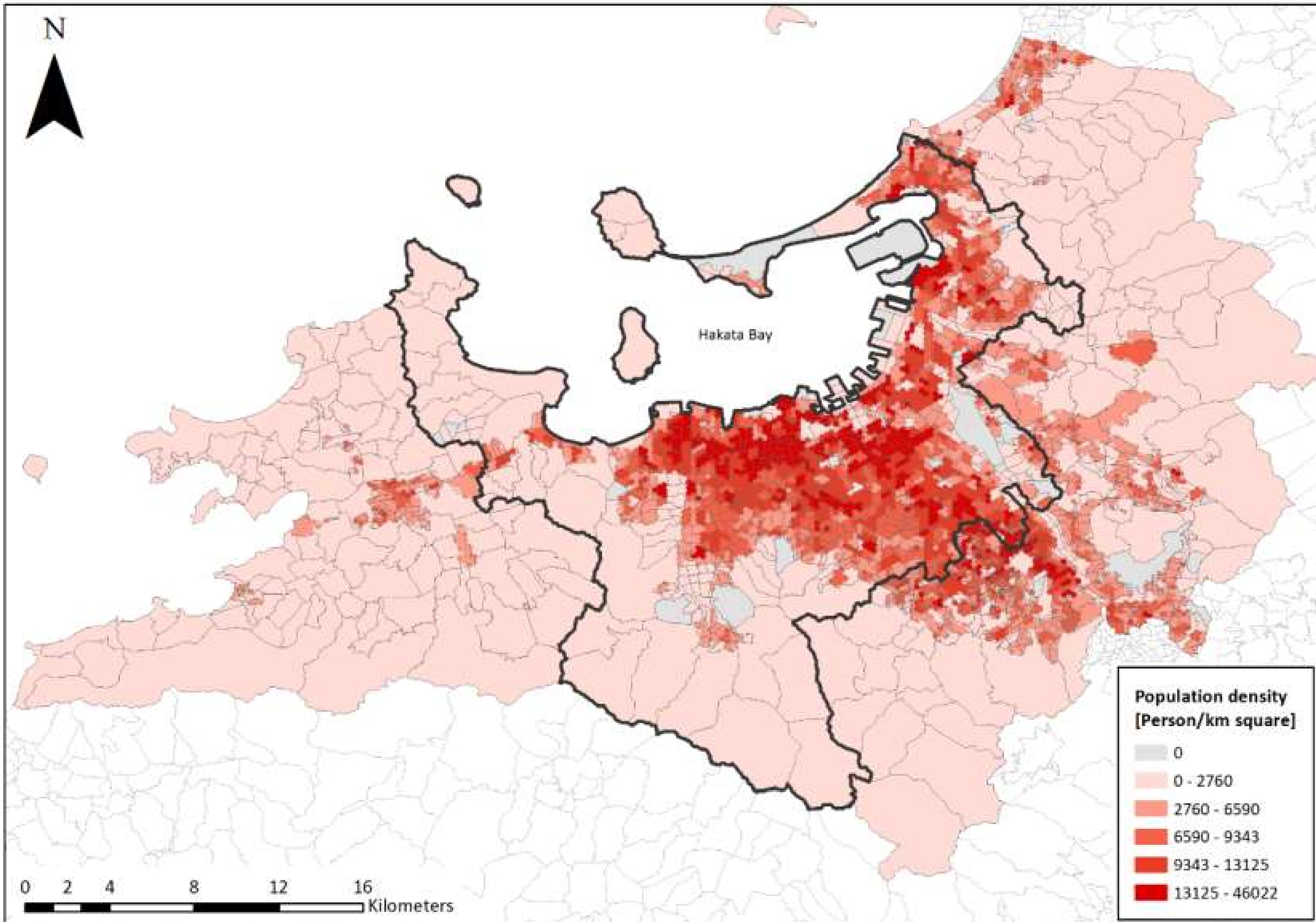
Model validation via a fixed-weight partial cross-validation test

COMMERCIAL KERNEL DENSITY

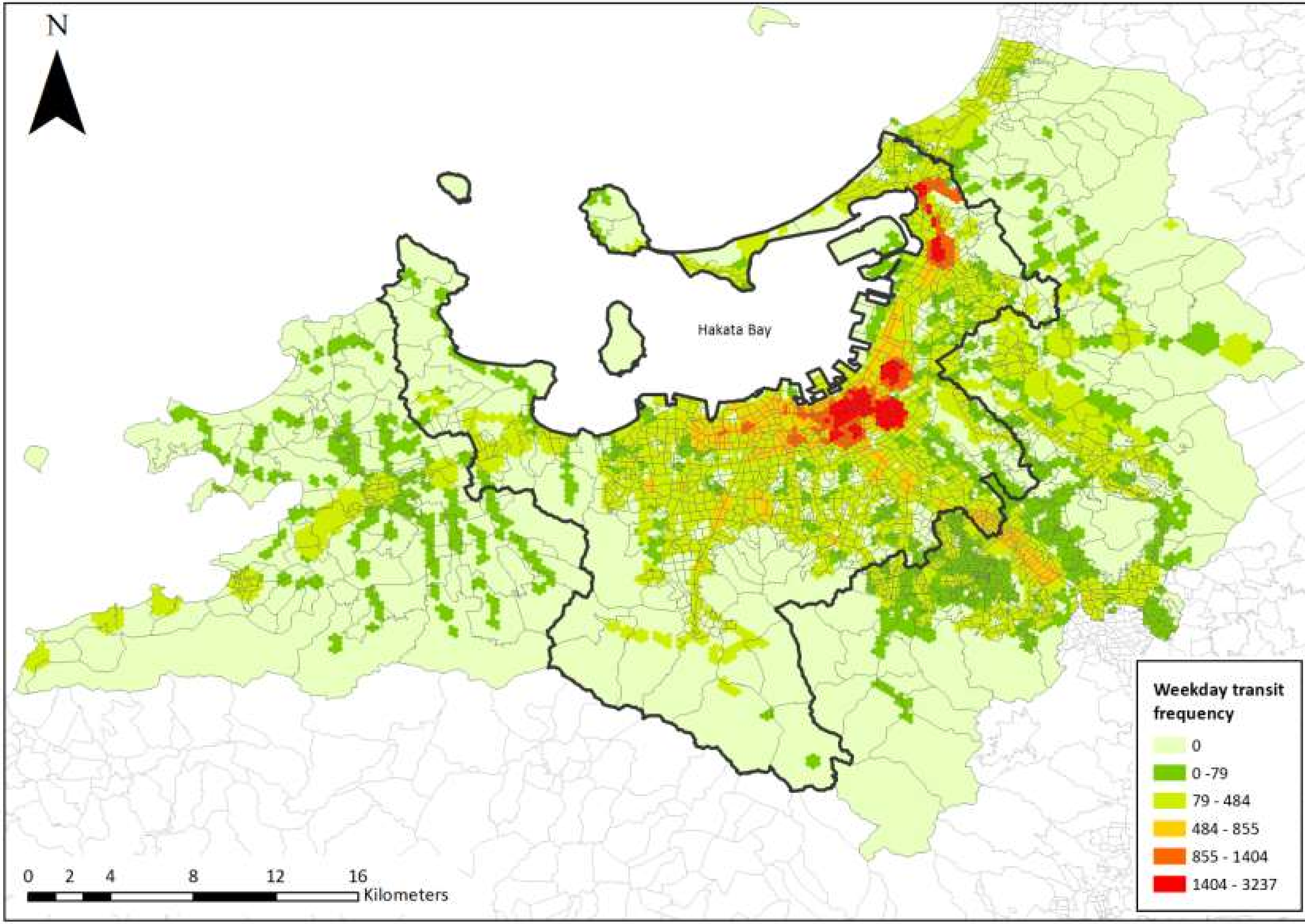
$$\hat{f}(x) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left\{\frac{1}{h}(\mathbf{x} - \mathbf{X}_i)\right\}$$



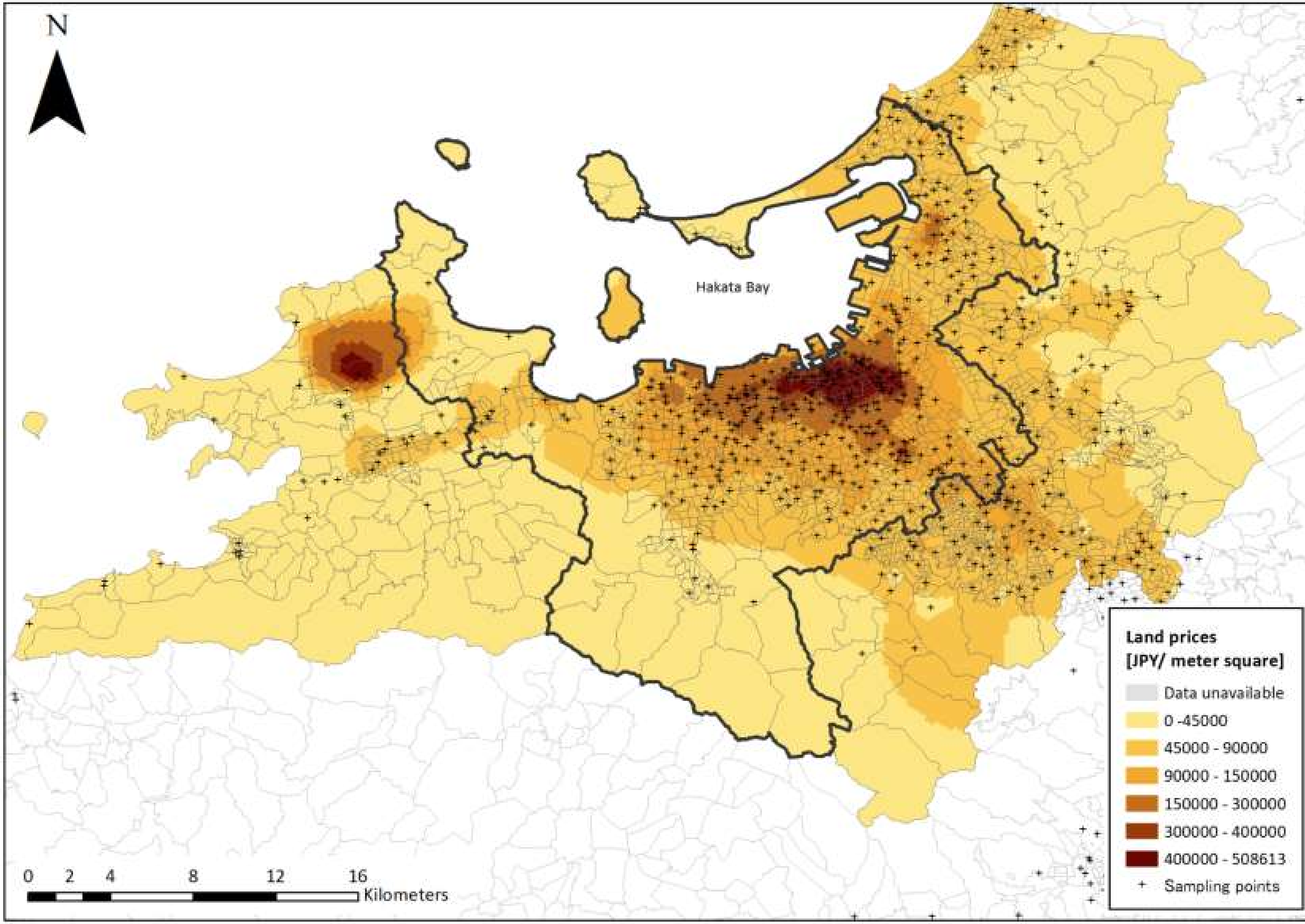
POPULATION DENSITY



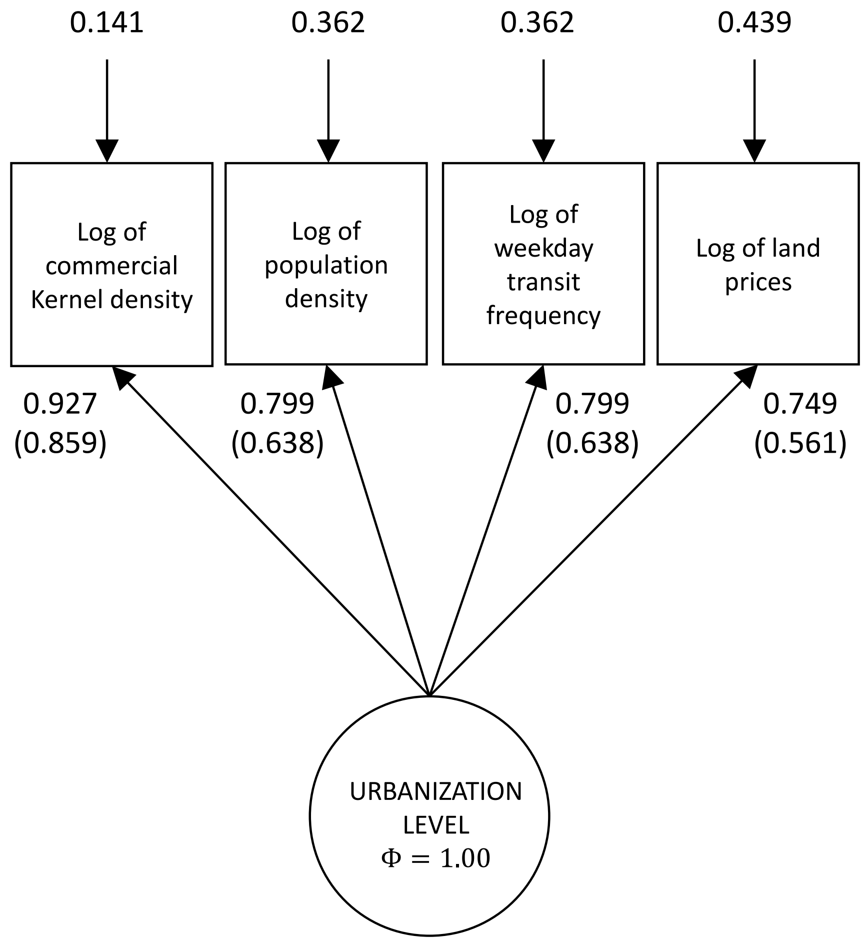
WEEKDAY TRANSIT FREQUENCY



LAND PRICES

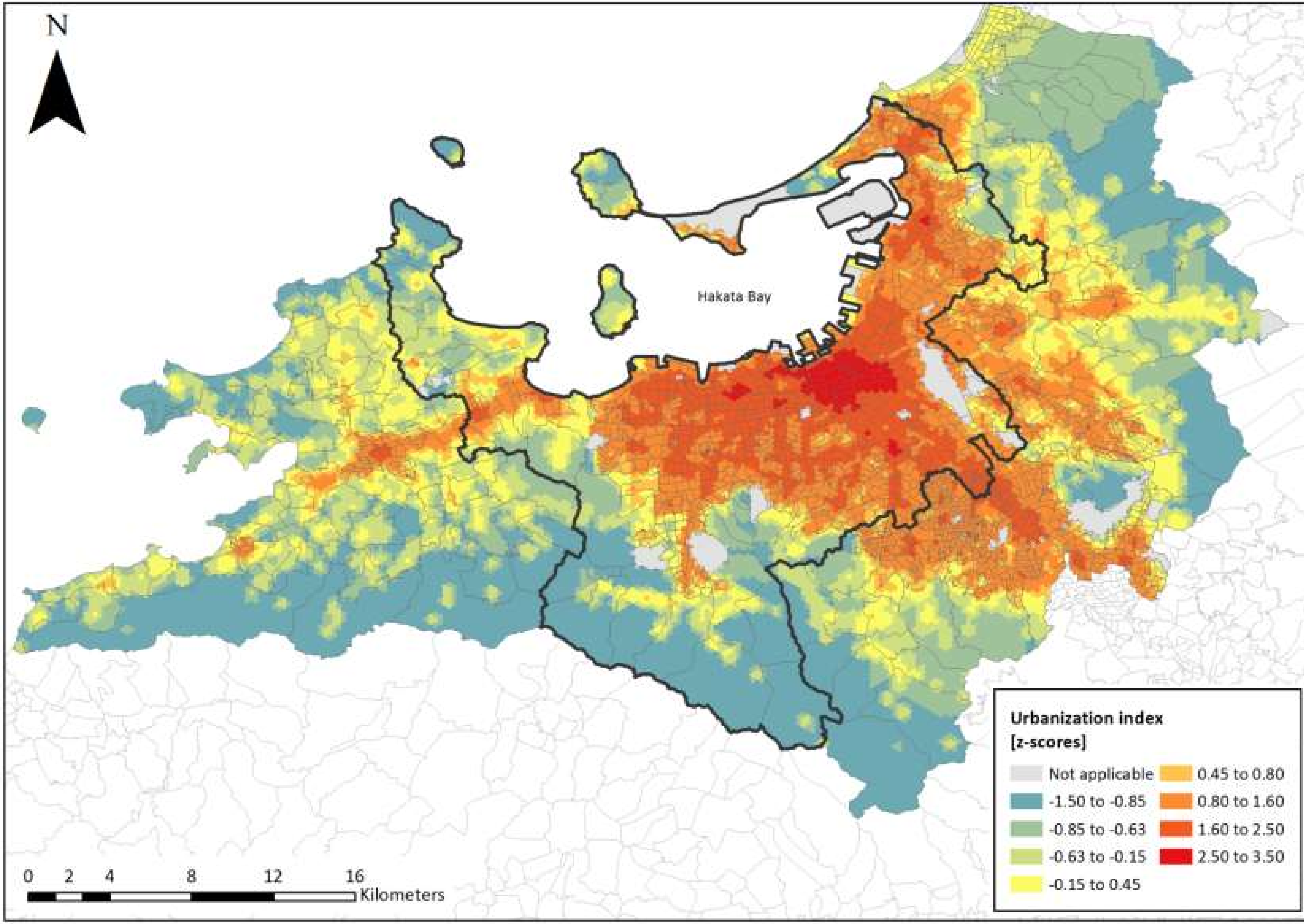

N
Hakata Bay
Land prices
[JPY/ meter square]
Data unavailable
0 -45000
45000 - 90000
90000 - 150000
150000 - 300000
300000 - 400000
400000 - 508613
Sampling points
0 2 4 8 12 16
Kilometers

MODEL RESULTS



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.

MODEL RESULTS



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SECTION 5

IMPLEMENTATION AND VALIDATION OF THE PROPENSITY SCORE: EMPIRICAL APPLICATION IN FUKUOKA CITY

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SECTION OBJECTIVES

① **Briefly summarize survey characteristics**

② **Measure the performance of the propensity score approach estimates against ordinary least squares estimates through Monte Carlo simulation**

③ **Estimate causal effects of the built environment on travel behavior using empirical data**

GENERAL CHARACTERISTICS OF THE SURVEY

- **Survey target:** Residents in Fukuoka city, Over 20 years old
- **Sampling criteria:** Stratified random sampling. Stratified on household structure (See Table 3 for details on sampling strata and population distribution)
- **Survey Medium:** Online survey
- **Survey period:** 2013年12月14日（土）～ 2013年12月16日（月）

SAMPLE HOUSEHOLD STRUCTURE DISTRIBUTION

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

METHODOLOGICAL COMPARISON THROUGH SIMULATION

GOAL: Use the survey data to simulate outcomes and compare the performance of OLS and propensity score stratification estimates in terms of **bias reduction.**

- Monte Carlo simulation (1000 iterations)

- **Exponential functions were used to specify two data generating processes (DGP):** (Following Thomas and Rubin (2000) and Imai and van Dyk (2004))

- Additive model of the form:

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

- Multiplicative model of the form:

$$\mathrm{Y_i} = \delta_i\, T_i^A + e^{\sum_{k=1}^{K} \lambda_k \boldsymbol{X}_{ik}}$$

δ_i= treatment effect

T_i^A=assigned treatment

$\boldsymbol{\Lambda}_k$ = vector of simulated coefficients N~(0,σ)

$\mathbf{X}_{ik}$ = vector of observed covariates in data *(of k dimensions)*

$$m = \begin{cases} +1 \\ -1 \end{cases}$$

METHODOLOGICAL COMPARISON THROUGH SIMULATION

- Specifying the variance of Λ_k **to control the level of linearity of the simulations**
  - **Highly linear** $R^2 \approx .95$
  - **Moderately linear** $R^2 \approx .85$
  - **Moderately non-linear** $R^2 \approx .75$
- Additive model of the form:

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

- Multiplicative model of the form:

$$\mathrm{Y_i} = \delta_i\, T_i^A + e^{\sum_{k=1}^{K} \lambda_k \boldsymbol{X}_{ik}}$$

δ_i= treatment effect
T_i^A=assigned treatment

$\boldsymbol{\Lambda}_k$ = vector of simulated coefficients (N~(0,σ)
$\mathbf{X}_{ik}$ = vector of observed covariates in data *(of k dimensions)*

$$m = \begin{cases} +1 \\ -1 \end{cases}$$

METHODOLOGICAL COMPARISON THROUGH SIMULATION

- **Constant treatment** models:
  - Assumes effect is the same for all individuals
- **Variable treatment** defined as a function of a covariate:

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

Where H is the car use habit index as measured by the Response Frequency Index method, and β_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.

Total simulated models: 144

PROPENSITY SCORE OLS ESTIMATION RESULTS - FUKUOKA

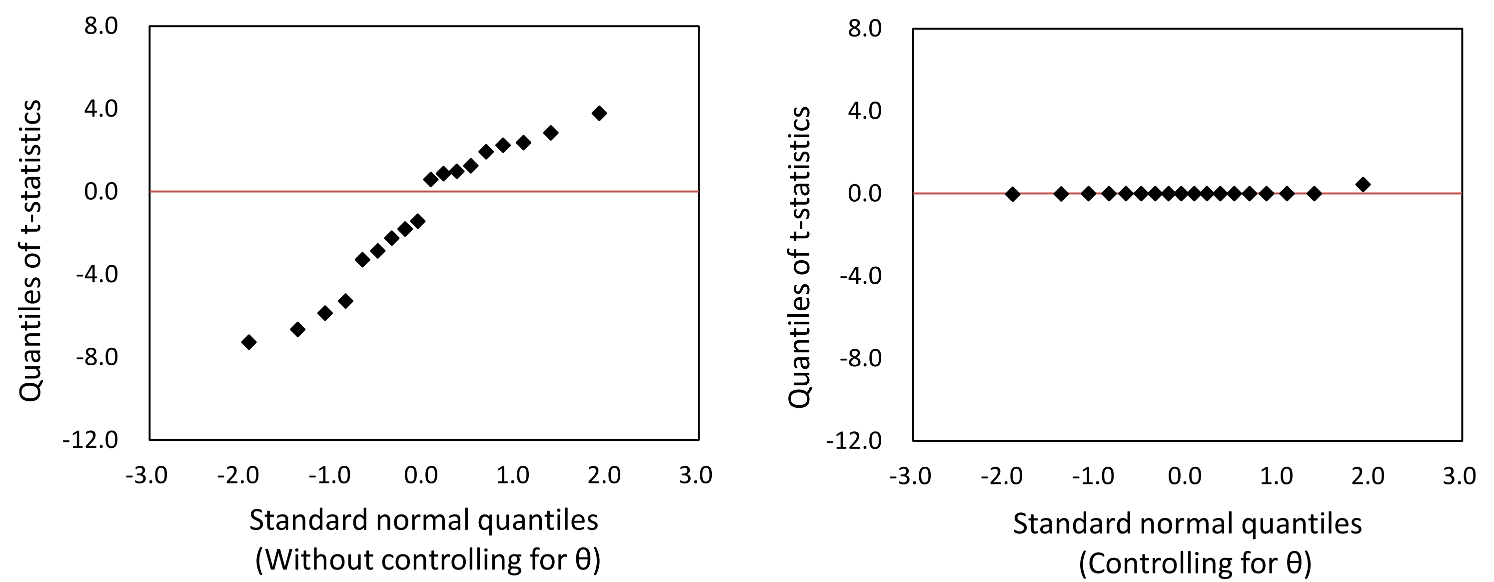
N	491	S.E. of e	0.5331
Parameters	19	R-square	0.25
d.f.	472	Adj. R-square	0.22
RSS	134.14	F test (p-value)	8.66 (.0000)

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

② Measure the performance of the propensity score approach via Monte Carlo simulation

PROPENSITY SCORE AS A BALANCING SCORE

STANDARD NORMAL QUANTILE PLOTS OF T-STATISTICS OF COVARIATES



The propensity score serves as a balancing score:

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

MEASURING THE PERFORMANCE OF THE PROPENSITY SCORE STRATIFICATION AGAINST OLS

- The performance of each model is compared against the OLS estimates, measured in terms of absolute bias where:

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

and mean squared error where:

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

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

② Measure the performance of the propensity score approach via Monte Carlo simulation

SIMULATED CHANGES IN ABSOLUTE BIAS AND MEAN SQUARED ERROR COMPARED AGAINST THE OLS ESTIMATES- 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%	[illegible]	-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%	[illegible]	-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

Positive values:
Bias increase
Relative to OLS

Negative values:
Bias decrease
Relative to OLS

② Measure the performance of the propensity score approach via Monte Carlo simulation

SIMULATED CHANGES IN ABSOLUTE BIAS AND MEAN SQUARED ERROR COMPARED AGAINST THE OLS ESTIMATES- 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%		-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%		-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

Positive values:
Bias increase
Relative to OLS

Negative values:
Bias decrease
Relative to OLS

② Measure the performance of the propensity score approach via Monte Carlo simulation

SIMULATED CHANGES IN ABSOLUTE BIAS AND MEAN SQUARED ERROR COMPARED AGAINST THE OLS ESTIMATES- 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%		-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%		-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

Positive values:
Bias increase
Relative to OLS

Negative values:
Bias decrease
Relative to OLS

② Measure the performance of the propensity score approach via Monte Carlo simulation

SIMULATED CHANGES IN ABSOLUTE BIAS AND MEAN SQUARED ERROR COMPARED AGAINST THE OLS ESTIMATES- 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%	[redacted]	-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%	[redacted]	-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

Positive values:
Bias increase
Relative to OLS

Negative values:
Bias decrease
Relative to OLS

SIMULATION RESULTS

- The propensity score achieves:
  - **Absolute bias reductions of up to 76%** against the OLS estimates.
  - **MSE reductions up to 94%** against the OLS estimates.

- Propensity score models with no covariates performed poorly, including covariates is recommended.

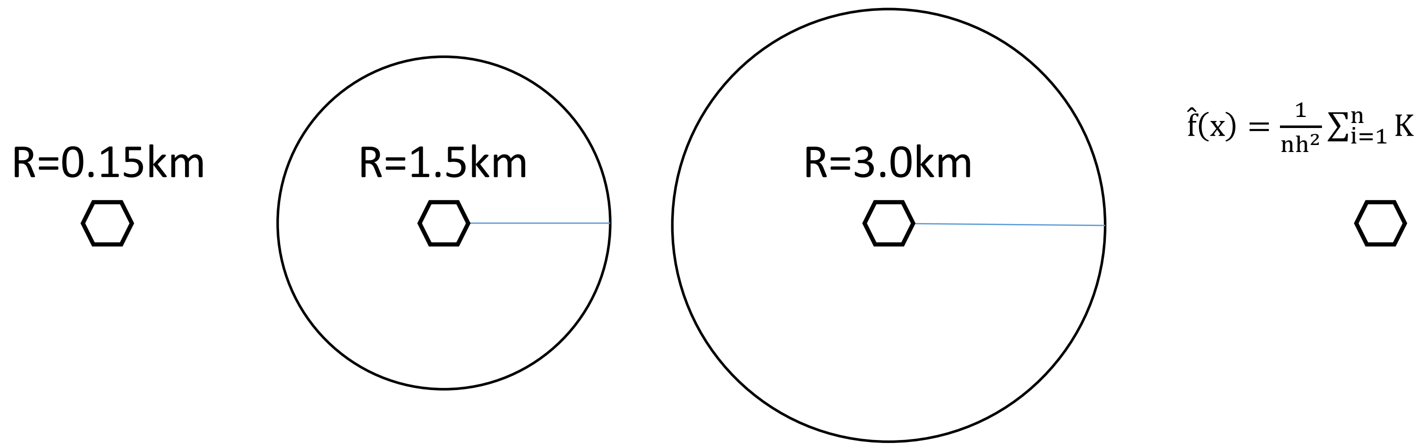
- For moderate sample sizes (400-600) stratification on 5 strata is recommended
  - This is most likely due to **sample size and multivariate distribution** of covariates (Imbens and Wooldridge 2008)

MULTI-SCALE ANALYSIS OF EMPIRICAL DATA

Having demonstrated the bias reduction potential of the propensity score approach, **the method is applied to the Fukuoka survey dataset**. In addition, a **multi-scale analysis is conducted**, largely motivated by the modifiable areal unit problem (Fotheringham & Wong, 1991).

Different scales of treatment considered:

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



Scale 1

Scale 2
(unweighted average)

Scale 3
(unweighted average)

Scale 4
(Kernel density function)

③ **Estimate causal effects** of the built environment on travel behavior using **empirical data**

MULTI-SCALE ANALYSIS OF EMPIRICAL DATA

MULTI-SCALE ANALYSIS OF URBANIZATION EFFECT ON HOME-BASED MAINTENANCE TRIPS

Treatment scale		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	0.002	-3.191	-5.020	-2.477	-4.106	-3.273	-5.110
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

		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
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

SUMMARY OF FINDINGS

- Under the ignorability of treatment assumption a **casual effect can be estimated using cross-sectional data**

- **Findings suggest the existence of a mode substitution mechanism between car and NMM** for non-work trips given changes in urbanization, as measured by the urbanization level index.

- For the **5 strata – Scale 4** case one standard unit increase of urbanization on average translates into:
  - **21% less home-based maintenance car trips**
  - **17% more home-based maintenance non-motorized trips**

- A multi-scale analysis suggest that **OLS is very sensitive to the scale of analysis** with difference in estimates of up to 100%.

A CAVEAT

- In terms of the propensity score function, the importance of the **strong ignorability of treatment assumption** cannot be over-emphasized. This assumption is crucial to the unbiasedness of estimates.

- In practice it **is impossible to know how well the estimated function approximates the true population function**.

- Although in order to estimate the propensity score function, **relevant variables largely cited in the literature introduced in the model**, 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.

- **Much care should be place in estimating the propensity score function**, as much of the validity of the analysis depends on it.

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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

ー日本の諸都市を事例としてー

SECTION 6

CONCLUSION

東京大学大学院工学系研究科都市工学専攻都市交通研究室

FINDINGS AND CONTRIBUTIONS

- **Operationalization of a continuous index to measure built environment characteristics.**
  - This index can then be used as a continuous treatment variable in propensity score estimations of causal effects using cross-sectional data.

- **Implementation and validation of a methodology to assess the causality problem from a cross-sectional approach.**
  - This approach relaxes the binary treatment assumption of the traditional propensity score approaches. **[First in the planning literature]**
  - The effectiveness of the proposed methodology in reducing bias against OLS was validated via Monte Carlo simulation.

- **Estimation of causal effects** of the built environment on travel behavior from **cross-sectional perspective**.

POLICY IMPLICATIONS

- In general, findings support the notion that the **built environment has a significant effect on travel behavior**, specifically, on trip frequency by mode.
- Data from Fukuoka city supports the notion that living in more urbanized areas is conducive to less car use and more non-motorized trips.
- Nevertheless, **the issue at hand is more complex that just retrofitting or promoting a certain (re)development model.** Even after establishing a causal relation, residential location is still a self-selecting process guided by household life stage, lifestyle and preferences, so a **mismatch between supply and demand might hamper efforts to promote compact city paradigms.**

FUTURE RESEARCH DIRECTIONS

- **Cross sectional analysis:**
  - **Gross misspecification of the propensity score function can result in serious bias** (Imai & van Dyk, 2004). Hence further research efforts should be directed towards **improving the propensity score estimates.**

- **Attitudes measurement and use as control variable**
  - **No overarching guiding theory**
  - Research efforts should thus be directed towards the **development of a theory that guides the attitudes and preference measurements** in the planning field.

FUTURE RESEARCH DIRECTIONS

- **Assessing other dimensions of travel behavior**
  - The main travel behavior dimension analyzed in this study relate to trip frequencies by mode.
  - **Other relevant dimensions** should be analyzed to strengthen the conclusions presented in this dissertation.
  - 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.

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都市の物的環境と交通行動の因果関係に関する研究
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Giancarlos Troncoso Parady

トロンコソ　パラディ　ジアンカルロス

東京大学大学院工学系研究科都市工学専攻都市交通研究室