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.*

![Diagram showing the relationship between Built environment and 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?
SECTION 2

LITERATURE REVIEW
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
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.
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—

SECTION 3
CROSS-SECTIONAL ANALYSIS AND THE CAUSALITY PROBLEM
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
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.

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

\[ \text{ATE} \rightarrow E[Y_{1i} - Y_{0i}] = E[Y_{1i}] - E[Y_{0i}] \]

Average treatment on treated

\[ \text{ATT} \rightarrow E[Y_{1i} - Y_{0i}|z_i = 1] = E[Y_{1i}|z_i = 1] - E[Y_{0i}|z_i = 1] \]

\[ E[Y_0|z = 1] \text{ however, is not observed. It’s a COUNTERFACTUAL!} \]

Where

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

\[ Y_{1i} = \text{Outcome when treated} \]
\[ Y_{0i} = \text{Outcome when untreated} \]
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

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

This we CANNOT observe

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

This we can observe

so we can substitute and get

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

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

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

\[\text{Selection Bias}\]

Under randomization \(Y_{0i}, Y_{1i} \perp z_i; \text{Bias} = 0\)
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 \( X \) \((Y_{0i}, Y_{1i} \perp z_i|X_i)\).

• 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:

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

(By CIA)

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

\[
= \frac{\sum_x \beta_x P(z_i = 1|X_i = x)P(X_i = x)}{\sum_x P(z_i = 1|X_i = x)P(X_i = x)}
\]

Where \( \beta_x = E[Y_{1i}|z_i = 1, X = x] - E[Y_{0i}|z_i = 0, X = x] \). That is, the difference of the mean between treated and untreated for any given value of \( x \).
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.
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 \( P(X_i) \), the distribution of \( X_i \) and \( z \) are independent

\[
P r\{ z_i | X_i, P(X_i) \} = Pr\{ z_i | P(X_i) \}
\]

The propensity score makes inherently different groups comparable
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 \( P(X_i) \). In addition, every unit has a chance to receive either treatment state

\[
P\{(Y_{0i}, Y_{1i})|z_i, P(X_i)\} = P\{(Y_{0i}, Y_{1i})|P(X_i)\}
\]

\[
0 < P(z_i = 1|P(X_i)) < 1
\]

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

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**

  \[
  ATE_{\text{matching}} = N^{-1} \sum_{i=1}^{N} \left\{ Y_{1i} - \sum_{j \in \{z=0\}} W_{N0N1}(i, j)Y_{0j} \right\}
  \]

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

- **WEIGHTING**

  \[
  ATE_{\text{weighting}} = N^{-1} \sum_{i=1}^{N} \left[ \frac{Y_i \cdot z_i}{P(X_i)} - \frac{Y_i \cdot (1 - z_i)}{1 - P(X_i)} \right]
  \]

- **STRATIFYING**

  \[
  ATE_{\text{stratification}} = \sum_{j=1}^{J} (\bar{Y}_{j1} - \bar{Y}_{j0}) \cdot W_j
  \]
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. :

- 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.
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 $T^A|X \sim N(X^\top \beta, \sigma^2)$
  
  • The propensity score function is solely characterized by the scalar $\theta_\psi(X) = X^\top \beta$ (The conditional mean function, estimated via OLS)
  
  • The propensity score serves as a balancing score:

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

  • Strong ignorability of treatment:

$$Pr\{Y(t^P)|T^A, P(X)\} = Pr\{Y(t^P)|P(X)\}$$
3. Introduction of a generalization of the propensity score to continuous treatments

GENERALIZING THE PROPENSITY SCORE TO CONTINUOUS TREATMENTS

- By averaging $\Pr\{Y(t^P) | P(X)\}$ 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** $\hat{\theta}$

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

where $\hat{\phi}_j$ is the within strata estimate of unknown parameter $\phi$ in strata $j$, and $W_j$ is the relative weight of strata $j$
The object of interest (ATE) is thus:

\[ \hat{\Phi} = \sum_{j=1}^{J} \hat{\phi}_j \{Y(t^P)|T^A = t^P, X\} \cdot W_j \]

Where \( \hat{\phi}_j \{Y(t^P)|T^A = t^P, X\} \) is the within strata estimated treatment parameter. Covariates \( X \) are included to control for variability of \( \theta \) within strata.
HYPOTHESIZED RELATION OF TREATMENT AND COVARIATES

Life stage → Lifestyle → Attitudes → Habits → Socio-demographics

Built environment at previous locations → Main mode of transport during previous life-stages

Work location

Residential Location choice: Built environment → Change in car ownership → Social network of ego

Subsistence activities → Maintenance activities → Discretionary activities → Travel behavior

RE-EXAMINING THE BUILT ENVIRONMENT-TRAVEL BEHAVIOR CONNECTION:
A CASE STUDY OF JAPANESE CITIES
SECTION 4

TREATMENT VARIABLE ESTIMATION: A LATENT CONSTRUCT OF URBANIZATION
THE CASE OF FUKUOKA CITY
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

\[
\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K\left\{\frac{1}{h}(x - x_i)\right\}
\]
POPULATION DENSITY

RE-EXAMINING THE BUILT ENVIRONMENT-TRAVEL BEHAVIOR CONNECTION: A CASE STUDY OF JAPANESE CITIES
WEEKDAY TRANSIT FREQUENCY

RE-EXAMINING THE BUILT ENVIRONMENT-TRAVEL BEHAVIOR CONNECTION: A CASE STUDY OF JAPANESE CITIES
LAND PRICES

RE-EXAMINING THE BUILT ENVIRONMENT-TRAVEL BEHAVIOR CONNECTION:
A CASE STUDY OF JAPANESE CITIES
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

RE-EXAMINING THE BUILT ENVIRONMENT-TRAVEL BEHAVIOR CONNECTION: A CASE STUDY OF JAPANESE CITIES
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—

SECTION 5

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

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

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
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

<table>
<thead>
<tr>
<th>Household type</th>
<th>Frequency</th>
<th>Sample percentage</th>
<th>Population percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single household</td>
<td>314</td>
<td>47.9%</td>
<td>47.7%</td>
</tr>
<tr>
<td>Of which: Young (age 20-64)</td>
<td>302</td>
<td>46.0%</td>
<td>39.2%</td>
</tr>
<tr>
<td>Of which: Elder (age 65 and over)</td>
<td>12</td>
<td>1.8%</td>
<td>8.5%</td>
</tr>
<tr>
<td>Couples only</td>
<td>101</td>
<td>15.4%</td>
<td>15.1%</td>
</tr>
<tr>
<td>Of which: Young (age 20-64)</td>
<td>60</td>
<td>9.1%</td>
<td>8.7%</td>
</tr>
<tr>
<td>Of which: Elder (age 65 and over)</td>
<td>41</td>
<td>6.3%</td>
<td>6.5%</td>
</tr>
<tr>
<td>Nuclear household (including single parent households)</td>
<td>201</td>
<td>30.6%</td>
<td>31.3%</td>
</tr>
<tr>
<td>Total</td>
<td>656</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

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:
  \[ Y_i = \delta_i T_i^A + \sum_{k=1}^{K} \lambda_k e^{m_k X_{ik}} \]

- Multiplicative model of the form:
  \[ Y_i = \delta_i T_i^A + e^{\sum_{k=1}^{K} \lambda_k X_{ik}} \]

- \( \delta_i \) = treatment effect
- \( T_i^A \) = assigned treatment
- \( \Lambda_k \) = vector of simulated coefficients \( N \sim (0, \sigma) \)
- \( m \) = \( \begin{cases} +1 \\ -1 \end{cases} \)
- \( X_{ik} \) = vector of observed covariates in data
  \((of \text{ k dimensions})\)
Measure the performance of the propensity score approach via Monte Carlo simulation

 METHODOLOGICAL COMPARISON THROUGH SIMULATION

- Specifying the variance of $\Lambda_k$ 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:
  $$Y_i = \delta_i T_i^A + \sum_{k=1}^{K} \lambda_k e^{m_k X_{ik}}$$

- Multiplicative model of the form:
  $$Y_i = \delta_i T_i^A + e^{\sum_{k=1}^{K} \lambda_k X_{ik}}$$

$\delta_i$ = treatment effect

$T_i^A$ = assigned treatment

$\Lambda_k$ = vector of simulated coefficients ($N \sim (0, \sigma)$)

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

$X_{ik}$ = vector of observed covariates in data (of $k$ dimensions)
② Measure the performance of the propensity score approach via Monte Carlo simulation

METHODOLOGICAL COMPARISON THROUGH SIMULATION

• **Constant treatment** models:
  
  • Assumes effect is the same for all individuals

• **Variable treatment** defined as a function of a covariate:

\[ \tilde{\delta}_m = 10^{-1} (10 - H) \delta_m \]

Where \( H \) is the car use habit index as measured by the Response Frequency Index method, and \( \beta_m \) 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

<table>
<thead>
<tr>
<th>N</th>
<th>491</th>
<th>S.E. of e</th>
<th>0.5331</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters</td>
<td>19</td>
<td>R-square</td>
<td>0.25</td>
</tr>
<tr>
<td>d.f.</td>
<td>472</td>
<td>Adj. R-square</td>
<td>0.22</td>
</tr>
<tr>
<td>RSS</td>
<td>134.14</td>
<td>F test (p-value)</td>
<td>8.66 (.0000)</td>
</tr>
</tbody>
</table>

### Variable | $\beta$ | S.E. | t-Stat
---|---|---|---
**Household characteristics**
Constant | 1.505 | 0.337 | 4.467
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
Measure the performance of the propensity score approach via Monte Carlo simulation

The propensity score serves as a balancing score:

\[ \Pr\{T^A|X, P(X)\} = \Pr\{T^A|P(X)\} \]
Measure the performance of the propensity score approach via Monte Carlo simulation

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:

\[
\bar{ABias} = \frac{1}{R} \sum_{r=1}^{R} (\hat{\delta} - \delta)
\]

and mean squared error where:

\[
\bar{MSE} = \frac{1}{R} \sum_{r=1}^{R} (\hat{\delta} - \delta)^2
\]

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

#### % Change in Absolute Bias

<table>
<thead>
<tr>
<th></th>
<th>3 Strata</th>
<th>5 Strata</th>
<th>7 Strata</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Additive models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>7.43%</td>
<td>-1.90%</td>
<td>-1.89%</td>
</tr>
<tr>
<td></td>
<td>-52.34%</td>
<td>-15.24%</td>
<td>-26.89%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>9.94%</td>
<td>-2.82%</td>
<td>0.42%</td>
</tr>
<tr>
<td></td>
<td>-51.25%</td>
<td>-13.63%</td>
<td>-27.67%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>6.08%</td>
<td>-2.12%</td>
<td>-3.12%</td>
</tr>
<tr>
<td></td>
<td>-16.03%</td>
<td>-27.09%</td>
<td></td>
</tr>
<tr>
<td><strong>Multiplicative models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>90.73%</td>
<td>-20.54%</td>
<td>22.33%</td>
</tr>
<tr>
<td></td>
<td>-41.93%</td>
<td>2.09%</td>
<td>-34.58%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>54.19%</td>
<td>-11.06%</td>
<td>5.59%</td>
</tr>
<tr>
<td></td>
<td>-40.21%</td>
<td>-4.28%</td>
<td>-12.54%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>17.14%</td>
<td>-17.68%</td>
<td>6.65%</td>
</tr>
<tr>
<td></td>
<td>-28.08%</td>
<td>2.28%</td>
<td>-10.91%</td>
</tr>
</tbody>
</table>

#### % Change in Mean Squared Error

<table>
<thead>
<tr>
<th></th>
<th>3 Strata</th>
<th>5 Strata</th>
<th>7 Strata</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Additive models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>36.36%</td>
<td>-5.17%</td>
<td>13.61%</td>
</tr>
<tr>
<td></td>
<td>-73.88%</td>
<td>-20.05%</td>
<td>-47.31%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>44.43%</td>
<td>-7.51%</td>
<td>20.41%</td>
</tr>
<tr>
<td></td>
<td>-72.30%</td>
<td>-15.76%</td>
<td>-48.76%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>33.26%</td>
<td>-5.13%</td>
<td>11.06%</td>
</tr>
<tr>
<td></td>
<td>-74.36%</td>
<td>-21.19%</td>
<td>-47.31%</td>
</tr>
<tr>
<td><strong>Multiplicative models</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>384.55%</td>
<td>-41.61%</td>
<td>131.18%</td>
</tr>
<tr>
<td></td>
<td>-70.69%</td>
<td>41.03%</td>
<td>-49.44%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>137.92%</td>
<td>-45.90%</td>
<td>9.11%</td>
</tr>
<tr>
<td></td>
<td>-4.41%</td>
<td>-45.50%</td>
<td></td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>19.32%</td>
<td>-49.49%</td>
<td>2.47%</td>
</tr>
<tr>
<td></td>
<td>-62.45%</td>
<td>-4.59%</td>
<td>-51.94%</td>
</tr>
</tbody>
</table>

**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)

<table>
<thead>
<tr>
<th></th>
<th>3 strata</th>
<th>5 strata</th>
<th>7 strata</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N.C.</td>
<td>A.C.</td>
<td>N.C.</td>
</tr>
<tr>
<td>% Change in absolute bias</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additive models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>91.45%</td>
<td>-20.17%</td>
<td>13.69%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>42.77%</td>
<td>-16.80%</td>
<td>3.80%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>41.74%</td>
<td>-3.95%</td>
<td>13.14%</td>
</tr>
<tr>
<td>Multiplicative models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>5.54%</td>
<td>-1.76%</td>
<td>-3.63%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>2.65%</td>
<td>-1.46%</td>
<td>-6.26%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>9.66%</td>
<td>-2.54%</td>
<td>0.13%</td>
</tr>
<tr>
<td>% Change in mean squared error</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additive models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>173.19%</td>
<td>-34.20%</td>
<td>23.96%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>69.67%</td>
<td>-42.41%</td>
<td>4.01%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>61.30%</td>
<td>-22.94%</td>
<td>12.58%</td>
</tr>
<tr>
<td>Multiplicative models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>36.44%</td>
<td>-5.62%</td>
<td>13.71%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>28.86%</td>
<td>-4.73%</td>
<td>7.41%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>40.15%</td>
<td>-6.19%</td>
<td>16.79%</td>
</tr>
</tbody>
</table>

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)**

<table>
<thead>
<tr>
<th></th>
<th>3 strata</th>
<th>5 strata</th>
<th>7 strata</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Change in absolute bias</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additive models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>71.56%</td>
<td>17.37%</td>
<td>-22.48%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>43.31%</td>
<td>5.39%</td>
<td>-5.28%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>13.46%</td>
<td>-0.57%</td>
<td>-3.98%</td>
</tr>
<tr>
<td>Multiplicative models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>83.80%</td>
<td>4.16%</td>
<td>-10.38%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>52.12%</td>
<td>-15.31%</td>
<td>-0.26%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>24.86%</td>
<td>-15.01%</td>
<td>7.74%</td>
</tr>
<tr>
<td><strong>Change in mean squared error</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additive models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>193.78%</td>
<td>37.61%</td>
<td>-39.72%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>87.20%</td>
<td>6.09%</td>
<td>1.98%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>36.40%</td>
<td>-4.15%</td>
<td>9.90%</td>
</tr>
<tr>
<td>Multiplicative models</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>385.66%</td>
<td>-1.44%</td>
<td>6.43%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>128.22%</td>
<td>-40.64%</td>
<td>1.95%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>27.17%</td>
<td>-45.21%</td>
<td>1.31%</td>
</tr>
</tbody>
</table>

**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)**

<table>
<thead>
<tr>
<th>Change in absolute bias</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3 strata</td>
<td>5 strata</td>
<td>7 strata</td>
<td>3 strata</td>
</tr>
<tr>
<td><strong>Additive models</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>71.74%</td>
<td>17.39%</td>
<td>-22.46%</td>
<td>-10.90%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>40.45%</td>
<td>4.83%</td>
<td>-6.05%</td>
<td>-31.68%</td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>12.27%</td>
<td>-1.04%</td>
<td>-3.37%</td>
<td><strong>49.34%</strong></td>
</tr>
<tr>
<td><strong>Multiplicative models</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>121.29%</td>
<td>-15.90%</td>
<td>16.92%</td>
<td>-33.12%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>49.74%</td>
<td>-24.81%</td>
<td>12.46%</td>
<td><strong>43.38%</strong></td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>55.90%</td>
<td>-22.06%</td>
<td>28.87%</td>
<td><strong>32.75%</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Change in mean squared error</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3 strata</td>
<td>5 strata</td>
<td>7 strata</td>
<td>3 strata</td>
</tr>
<tr>
<td><strong>Additive models</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>194.43%</td>
<td>37.67%</td>
<td>-39.70%</td>
<td>-20.80%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>80.91%</td>
<td>6.03%</td>
<td>-0.14%</td>
<td><strong>59.00%</strong></td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>39.71%</td>
<td>-4.94%</td>
<td>13.05%</td>
<td><strong>72.74%</strong></td>
</tr>
<tr>
<td><strong>Multiplicative models</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Highly linear</td>
<td>210.75%</td>
<td>-40.19%</td>
<td>16.72%</td>
<td>-71.60%</td>
</tr>
<tr>
<td>Moderately linear</td>
<td>152.05%</td>
<td>-41.89%</td>
<td>45.23%</td>
<td><strong>72.62%</strong></td>
</tr>
<tr>
<td>Moderately non-linear</td>
<td>209.94%</td>
<td>-40.94%</td>
<td>100.00%</td>
<td><strong>64.68%</strong></td>
</tr>
</tbody>
</table>

**Positive values:** Bias increase Relative to OLS  
**Negative values:** Bias decrease Relative to OLS  

*N.C.: No covariates; A.C.: All Covariates*
Measuring the performance of the propensity score approach via Monte Carlo simulation

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

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:

- **Scale 1**: R=0.15km (unweighted average)
- **Scale 2**: R=1.5km (unweighted average)
- **Scale 3**: R=3.0km (unweighted average)
- **Scale 4**: Kernel density function

\[ \hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K \left\{ \frac{1}{h} (x - X_i) \right\} \]
MULTI-SCALE ANALYSIS OF URBANIZATION EFFECT ON HOME-BASED MAINTENANCE TRIPS

<table>
<thead>
<tr>
<th>Treatment scale</th>
<th>Scale 1</th>
<th>Scale 2</th>
<th>Scale 3</th>
<th>Scale 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>OLS</td>
<td>5 Strata</td>
<td>OLS</td>
<td>5 Strata</td>
</tr>
<tr>
<td>Car trip frequency model</td>
<td>β</td>
<td>-0.201</td>
<td>-0.145</td>
<td>-0.217</td>
</tr>
<tr>
<td>NMM trip frequency model</td>
<td>β</td>
<td>0.151</td>
<td>0.125</td>
<td>0.156</td>
</tr>
<tr>
<td></td>
<td>t-Stat</td>
<td>2.595</td>
<td>1.924</td>
<td>2.710</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>OLS</th>
<th>7 Strata</th>
<th>OLS</th>
<th>7 Strata</th>
<th>OLS</th>
<th>7 Strata</th>
<th>OLS</th>
<th>7 Strata</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car trip frequency model</td>
<td>β</td>
<td>-0.201</td>
<td>-0.145</td>
<td>-0.223</td>
<td>-0.127</td>
<td>-0.205</td>
<td>-0.131</td>
<td>-0.217</td>
</tr>
<tr>
<td>NMM trip frequency model</td>
<td>β</td>
<td>0.151</td>
<td>0.125</td>
<td>0.181</td>
<td>0.089</td>
<td>0.172</td>
<td>0.103</td>
<td>0.187</td>
</tr>
<tr>
<td></td>
<td>t-Stat</td>
<td>2.595</td>
<td>1.924</td>
<td>2.989</td>
<td>1.215</td>
<td>3.023</td>
<td>1.746</td>
<td>3.245</td>
</tr>
</tbody>
</table>
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%.
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.
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—

SECTION 6
CONCLUSION
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 than 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.
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