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On the effect of the built environment and preferences on non-work travel: Evidence from Japan

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This study uses data from the 4th Nationwide Person Trip Survey to analyse the relation between the built environment, modal access preference at residential location and travel behaviour in Japan. By estimating random parameter count models, significant statistical associations were found between the built environment and preferences with non-work trip frequency by mode. Furthermore the effect of population density, car ownership and some access preference traits were found to be heterogeneous for some modes.
Since most of the recent literature has focused largely on North-American and European cities, this study contributes to the existing body of literature by examining the role of the built environment and individual preferences on travel behaviour in the context of Japanese cities, and sheds some light on existing heterogeneity in the effects of some factors related to travel behaviour.

Keywords: *Built environment, modal access preference, random parameter models, self-selection, travel behaviour, unobserved heterogeneity*

1. Introduction

In recent years, concepts such as smart growth, compact cities and new urbanism have penetrated the sustainability discourse under the premise that high density mixed-use cities might significantly reduce car use and improve both the liveability of cities and the health of its inhabitants. Although a large number of studies have attempted to clarify the relationship

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between the built environment and travel behaviour, evidence is still inconclusive. This article aims at contributing to the ongoing discussion by providing empirical results on the relationship between built environment and individual preferences with non-work trip frequency by mode in the context of Japanese cities. The rest of this paper is structured as follows. Section 2 provides an overview of the existing literature on the subject. Section 3 describes the characteristics of the data used, while Section 4 elaborates on the model structure and results. Finally Section 5 discusses findings and summarizes relevant conclusions.

2. Literature review

A considerable number of studies have attempted to clarify the relationship between the built environment and travel behaviour, and assess the magnitude of this effect. Although factors such as population density and land use mix have been consistently associated with lower levels of car use (Friedman, et al., 1994; Cervero & Radisch, 1996; Cervero & Kockelman, 1997), findings are rather mixed. Meta-analyses conducted by Leck (2006) and Ewing and Cervero (2010) found strong associations between land use mix and travel behaviour, but had somewhat different findings regarding the role of density. Whereas Leck argued that residential density is the most important built environment feature influencing travel behaviour, Ewing and Cervero suggested that after controlling for measures of accessibility to destinations, land use mix and street network characteristics, the effects of population and job densities are relatively weak.

Recent research has also pointed to individual preferences and attitudes as possible mediating factors between the built environment and travel behavior. Attitudes and preference research has been largely motivated by attempts to control for residential self-selection, that is, when the residential location decision is made partly in order to satisfy certain transportation preferences (Boarnet & Crane, 2001). To the extent that self-selection exists, failure to control for it makes built environment variables endogenous to the error term, thus rendering estimated parameters biased and inconsistent in most linear-in-parameters modeling approaches. To control for self-selection, it is reasonable to think of the residential self-selection bias as a form of omitted variable bias. In principle, by taking the variables that account for self-selection out of the error term and into the explanatory variables, the correlation between the regressors and the error is eliminated, thus solving or at least mitigating the endogeneity problem. In that sense, the main premise behind the need to control for individual attitudes and preferences is that by doing so the factors that drive residential location can be accounted for to some extent.

Although fully controlling for residential self-selection is out of the scope of this article, the issue will be touched upon several times when discussing individual attitudes and preferences as both issues are inherently intertwined. However, interested readers are referred to Mokhtarian & Cao (2008) and Cao et al. (2009a) for two thorough reviews on the issue. In addition, the literature discussed here will mainly focus on non-work travel research (unless specifically noted) as well as research directly related to Japan.

The most widely used approach to control for attitudes was proposed by Kitamura et al. (1997), who used factor analysis to extract a set of factors associated with travel attitudes, personality and lifestyle preferences (see Bohte et al. (2009) for a detailed review on attitudes-related research methodologies). Although considering all trip purposes, their study suggested that including individual attitudes and preferences in the model reduced the estimated magnitude of the effect of land use on trip frequency and trip mode ratio. Furthermore, individual attitudes and preferences explained a higher proportion of the variation in the data. Modelling specifically non-work trips, Chatman (2009) noted that if well self-selection might reduce the magnitude of the built environment effect, it does not render it insignificant.

After controlling for attitudes and preferences, Cao et al. (2006) suggested that while pedestrian shopping trips are more likely explained by self-selection, neighbourhood perception was a better prediction of strolling frequency. Similarly, Frank et al. (2007) found that individuals matching their walkable neighbourhood preference walked more for both discretionary and non-discretionary trips. Individuals preferring non-walkable environments were also found to walk less regardless of neighbourhood features. Additional evidence by Cao et al. (2009b) pointed out to the existence of a mode substitution mechanism between car and non-motorized modes given land use mix characteristics. Using non-transport-related residential preferences as instruments for type of neighbourhood, Khattak and Rodriguez (2005) found that households in neo-traditional neighbourhoods exhibit similar number of overall trips but fewer car trips.

Regarding literature on Japan, statistical associations have also been found between built environment and travel behaviour. Sun et al. (2009) pointed out that while overall trip number might be better predicted by household life-cycle stage, land use mix and density are better predictors of travel mode. A series of studies in the Osaka Metropolitan Area also suggested higher auto ownership for residents in suburban areas and areas with lower land use mixes (Senbil, et al., 2009; Sun, et al., 2012). In terms of non-motorized travel, studies in the medical field have found positive associations between perception of neighbourhood aesthetics and higher levels of leisure walking, while neighbourhood characteristics such as density and land use mix were associated with walking for transport (both work and non-work purposes) (Kondo, et al., 2009; Inoue , et al., 2010).

Through propensity score stratification with urbanization level as treatment variable, Troncoso Parady et al. (2014a) found evidence of a substitution effect between car and non-motorized modes given changes in urbanization level in Hiroshima city. Using panel data, Troncoso Parady et al. (2014b) analysed through a fixed effect model changes in travel behaviour in residents moving to a new high-density compact development in Chiba, Japan. Findings also evidenced a substitution effect between frequencies of nearby activities reached by non-motorized modes and faraway activities reached by car given changes in accessibility levels around home location, although effects were dependent on activity type.

3. Data and study variables

Data from the 4th Nationwide Person Trip Survey conducted in 2005 by the Ministry of Land, Infrastructure, Transport and Tourism of Japan (MLIT, 2005) was used for this analysis. The study surveyed 32,000 respondents across 62 cities all over japan, selected according to their urban characteristics (See Table 1). One day travel data for both weekdays and weekends were collected via a travel diary. Additionally, data from a separate attitude questionnaire conducted along with the main survey on a sub-sample of 9,400 was used to gather data on modal accessibility preference at the time of the respondents' last move. Out of this sub-sample, cities for which the whole set of independent variables was not available were excluded from the analysis, resulting in an effective sample of 7408 individuals across 57 cities.

Table 1. Cities surveyed in the 4th Nationwide Person Trip Survey

Group	Type[1]	Name
Three major metropolitan areas	Central	Saitama, Chiba, Tokyo, Yokohama, Kawasaki, Nagoya, Kyoto, Osaka, Kobe*
	Other	Toride, Tokorozawa, Matsudo, Inagi, Sakai*, Nara, Ome, Gifu, Kasugai, Kameyama, Omihachiman, Uji
Regional urban areas I (Population of central cities over one million)	Central	Sapporo*, Sendai, Hiroshima, Kitakyushu, Fukuoka
	Other	Otaru*, Chitose*, Shiogama, Kure, Otake, Dazaifu
Regional urban area II (Population of central cities over 400,000)	Central	Utsunomiya, Kanazawa, Shizuoka, Matsuyama, Kumamoto, Kagoshima
	Other	Oyabe, Komatsu, Iwata, Soja, Isahaya, Usuki
Regional urban area III (Population of central cities under 400,000)	Central	Hirosaki, Morioka, Koriyama, Matsue, Tokushima, Kochi
	Other	Takasaki, Yamanashi, Kainan, Yasugi, Nangoku, Urasoe
Regional area		Yuzawa, Ina, Joetsu, Nagato, Imabari, Hitoyoshi

Adapted from MLIT (2007)
*Cities excluded from analysis due to data unavailability

3.1 Dependent Variables

Three dependent variables were used in this study to describe individual travel behaviour: Number of home-based non-work trips[6] by private vehicle, number of home-based non-work trips by public transport, and number of home-based non-work trips by non-motorized modes. For each mode, trip frequency is calculated as the sum of trips for one weekday and one weekend. Given that the present analysis focuses on modelling trip frequencies, work trips were excluded since commuting trip frequency is in general determined by factors other to the built environment.

In the two-day period that the survey accounts for (one weekday and one weekend), car trips accounted for 67% of all non-work trips, followed by non-motorized trips and transit trips with respective shares of 27% and 6%. The assignment criterion for segmented trips was based on a representative mode hierarchy, where mode assignment priority was given first to public transport, followed by private vehicle and finally to non-motorized modes. For example, if the *i*th individual used all three modes to reach her destination, the trip is registered as a transit trip; if she used car and non-motorized modes, the trip is registered as a car trip and so on.

3.2 Independent Variables

The analysis scale of built environment variables followed the survey districts defined in the person trip survey, which constitute an aggregation of several blocks (In Japanese *Aza* or *Cho*). The average area of these districts is 1.14 km^2 with a standard deviation of 2.96 km^2.

Gross population density and commercial density were used as indicators of land use intensity and mix. Commercial density was defined as the number of non-industrial service facilities in a given district. Commercial data was extracted from the geo-referenced phonebook data provided by ZENRIN Co., Ltd (2011). As a measure of access to transit, a binary variable was specified to take value "1" if residential location is within 800m from a train station and "0" otherwise. Distance to station was estimated as the distance "as the crow flies" from each district centroid.

[6] Non-work trips include all non-commuting trips such as shopping, eating-out, leisure and maintenance, but exclude return-home trips.

Regarding preference variables, data from the aforementioned attitude survey was used. Respondents were asked to rate on a five point Likert Scale the level of consideration given to six factors when choosing their current residential location, with "1" indicating that the factor was not considered at all, and "5" indicating that the factor was considered very much. For this analysis, those factors directly related to modal access preference were selected:

- Ease of use of public transport
- Ease to meet daily needs by walking or biking to destinations around home
- Ease of travel by car

Binary coded variables were generated as non-mutually exclusive preference indicators, where responses indicating high preference for a given mode (fourth and fifth levels of the Likert Scale) were coded as "1", and all other values coded "0". Table 2 summarizes respondents' modal access preferences when choosing current residential location. Given that categories are non-mutually exclusive, joint preferences are also presented. Finally, Table 3 summarizes the descriptive statistics of the variables relevant to this study.

Table 2. Modal access preferences when choosing current residential location

Access Preference	Frequency	N	Relative Frequency
Car	3911	7407	0.53
Public transport	4627	7407	0.62
Non-motorized	4648	7407	0.63
Joint Preferences			
Car + PT	2840	7407	0.38
Car + NMT	2941	7407	0.40
PT + NMT	3819	7407	0.52
All modes	2471	7407	0.33

Table 3. Descriptive Statistics of variables

Variable Name	Mean	Std.Dev.	Minimum	Maximum
Dependent variables[1]				
Number of non-work trips	1.28	1.05	0	9
Number of car non-work trips	0.86	0.94	0	6
Number of transit non-work trips	0.08	0.30	0	3
Number of non-motorized non-work trips	0.35	0.69	0	6
Socio-demographic variables				
Male	0.47	-	-	-
Age	48.77	15.40	18	101
Worker	0.62		-	-
Household size	3.06	1.23	1	10
Nuclear household (Excludes mono-parental households)	0.37	-	-	-
Single household	0.08	-	-	-
Young couple (Under 65 years old)	0.16	-	-	-
Transport mean ownership				
Number of bicycles in household	1.42	1.39	0	10
Number of cars in household	1.68	1.11	0	12
Built environment characteristics				
Log of population density	8.49	1.01	3	10.49
Log of commercial density	4.58	1.40	0	8.84
Train station within 800m	0.35	0.48	0	1

[1]Reported trip frequencies include one weekday and one weekend

4. Model structure and results

4.1 Model specifications

Count data models have been widely used in transportation planning to model trip frequencies as these models properly account for the non-negative, finite and integer nature of the data (e.g. Chatman, 2009; Cao, et al., 2006; Khattak & Rodriguez, 2005) as illustrated in Figure 1.

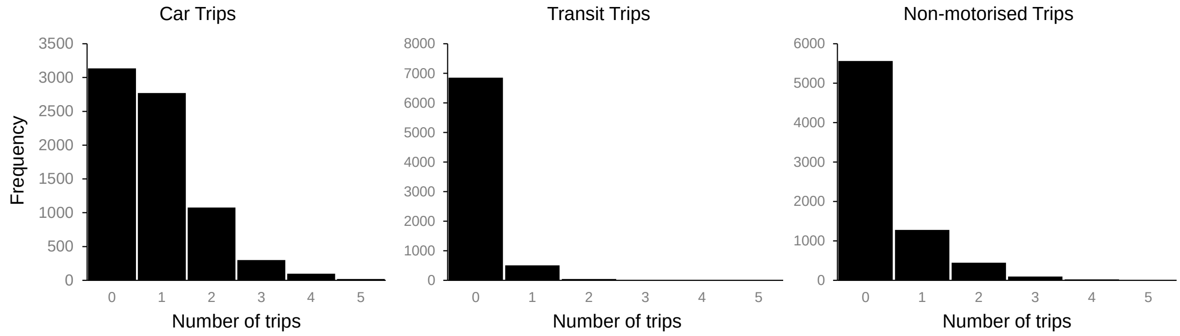

Figure 1. Histogram of non-work trips by mode

Departing from the basic Poisson regression model, several extensions have been developed to account for heterogeneity in the data. The simplest extension is the negative binomial regression, which relaxes the equi-dispersion condition of the Poisson model, and estimates the distribution variance as a function of a dispersion parameter; this parameter can also be specified as a function of observed covariates.

Since data from 57 cities spread all over the country were used for this analysis, heterogeneity stemming from unobserved variations in city characteristics is a non-trivial issue. In that sense, it is hypothesized that the average effect of variables associated with the built environment and preferences are not constant across cities. To account for this unobserved heterogeneity, random parameter Poisson regressions (or negative binomial regressions where the equi-dispersion condition is not met) are specified, where the conditional mean function is in the Poisson case

$$Y|\boldsymbol{v}_{i,c} = e^{\beta'_{i,c}\boldsymbol{X}_{i,c}} \quad (1)$$

and in the negative binomial case

$$Y|\boldsymbol{v}_{i,c} = e^{\beta'_{i,c}\boldsymbol{X}_{i,c}+\varepsilon_i} \quad (2)$$

given

$$\beta_{i,c} = \beta + \boldsymbol{\Gamma}\boldsymbol{v}_{ic} \quad (3)$$

where β is the deterministic component and defines the fixed mean of the distribution of the random parameter. The random component is defined by $\boldsymbol{\Gamma}\boldsymbol{v}_{ic}$ where $\boldsymbol{v}_{it}$ is a set of latent random terms in the ith observation in group c in $\beta_{i,c}$, where c encompass the cities listed in Table 1, thus resulting in 57 groups.

Conceptually, instead of assuming that estimated parameters are constant across all cities, unique intercepts and parameter slopes are specified for each city, thus allowing for inter-city variations in the parameter estimations due to unobserved heterogeneity. To avoid theoretically inconsistent sign changes in the parameter estimates (likely to occur when assuming a normal distribution for the latent random terms), the range of the parameters were restricted by assuming a triangular distribution constrained to zero at one end of the distribution and a spread equal to two times the estimated mean (Greene, 2007). [7]

As shown by Greene (2005), the conditional mean effect for specific cities is estimated as

$$\hat{E}(\beta_{i,c}|Y_i,\boldsymbol{X_i}) = \frac{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{\beta}_{i,c,r}\hat{L}(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,\beta,r}})}{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{L}(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,\beta,r}})} \tag{4}$$

where $\hat{L}(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,\beta,r}})$ is the contribution to the likelihood function of individual i evaluated at all estimated parameters and the r^{th} simulated unconditional estimate $\hat{\beta}_{i,c,r}$. For each random parameter, the standard deviation of the distribution is estimated as

$$\widehat{S.D.}(\beta_{i,c}|Y_i,\boldsymbol{X_i}) = \sqrt{\hat{E}(\beta_{i,c}^2|Y_i,\boldsymbol{X_i}) - \left(\hat{E}(\beta_{i,c}|Y_i,\boldsymbol{X_i})\right)^2} \tag{5}$$

where $\hat{E}(\beta_{i,c}^2|Y_i,\boldsymbol{X_i})$ is the conditional expected square estimated as

$$\hat{E}(\beta_{i,c}^2|Y_i,\boldsymbol{X_i}) = \frac{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{\beta}^2{}_{i,c,r}\hat{L}(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,t,\beta,r}})}{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{L}(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,t,\beta,r}})} \tag{6}$$

To evaluate the goodness of fit of the models, and following Cameron & Windmeijer (1996), R-squared statistics based on the deviance residuals for both the Poisson and negative binomial models were calculated where:

$$R_{DEV\ Poisson}^2 = 1 - \frac{\sum_{i=1}^{N}\left\{y_i \log\left(\left(\frac{\hat{\mu}_i}{\bar{y}}\right) - (\hat{\mu}_i - \bar{y})\right)\right\}}{\sum_{i=1}^{N}\left\{y_i\, log\left(\frac{y_i}{\bar{y}}\right)\right\}} \tag{7}$$

and

$$R_{DEV\ NegBin2}^2 = 1 - \frac{\sum_{i=1}^{N}\left\{y_i\, log\left(\frac{y_i}{\hat{\mu}_i}\right) - (y_i + \hat{\alpha}^{-1})log\left(\frac{y_i + \hat{\alpha}^{-1}}{\hat{\mu}_i + \hat{\alpha}^{-1}}\right)\right\}}{\sum_{i=1}^{N}\left\{y_i\, log\left(\frac{y_i}{\bar{y}}\right) - (y_i + \hat{\alpha}^{-1})log\left(\frac{y_i + \hat{\alpha}^{-1}}{\bar{y} + \hat{\alpha}^{-1}}\right)\right\}} \tag{8}$$

Where $\hat{\mu}_i$ are fitted values of y_i, $\bar{y}_i$ the fitted mean, and $\hat{\alpha}$ the estimated overdispersion parameter in the negative binomial case.

For each mode, three models were specified: a base model containing only socio-demographic variables (S.D. model), a built environment model which includes all built environment features in addition to socio-demographics (B.E. Model), and a full model which includes all variables, including preferences (Full Model).

4.2 Model estimation results

Random parameter Poisson models were estimated for the car trip and transit trip frequency models, while in the non-motorized case random parameter negative binomial models were estimated. Models were estimated based on 200 Halton draws, as it has been empirically demonstrated to provide the same level of simulation performance as purely random draws at considerably smaller number of draws (Bhat, 2003). The initial specification set all built environment and preference variables as random parameters. Among socio-demographics, number of cars in household was also set as random, as its effect on travel behaviour was

[7] It is important to note that the assumed distribution of the random terms is rather arbitrarily defined, and results might be sensitive to different specifications, especially if the distribution spread is constrained.

assumed to vary given city characteristics. Greene (2005) notes that in the case of random parameter models, the t-statistic alone might not be enough to conclude that the relationship of interest is insignificant, so in addition to the t-statistics, the coefficients' 95% confidence intervals were used to assess the difference in parameters across cities. In that sense, Departing from the initial specification, random parameters that were not statistically significant and whose confidence intervals exhibited little variation among groups were fixed across groups and the models were re-estimated[8].

Estimation results evidenced the existence of unobserved heterogeneity in the built environment and preference effects in all models. Final estimation results are summarized in Table 4, while Figure 2 illustrates the 95% confidence intervals of the estimated random parameters for each city. For comparison purposes, the horizontal lines plot the fixed parameter estimation in each case.

All else equal and regardless of travel mode, men carried on average less non-work trips than women. Similarly, worker status was associated with less non-work trips irrespective of mode; this difference was considerably larger for non-motorized trips. In terms of household structure composition, belonging to a nuclear household was positively associated with car trip frequency and negatively associated with transit frequency, while living alone was associated with less car travel and more non-motorized trips. Positive and significant associations were also observed between young couple households and both car and non-motorized trips.

Regarding built environment characteristics, fixed across all observations, the elasticity of commercial density on non-motorized trips suggests a 0.075% increase in trip frequency for every 1% increase in commercial density, a rather inelastic effect. Living within 800 metres from a transit station was associated with an average of 8% less car trips and conversely 8% more non-motorized trips. In terms of transit trip frequency, although only significant at the 0.1 level, the living near a transit station was associated with 15% more transit trips.

In terms of random parameters, estimated values reported in Table 4 are of not very informative, as the objects of interest are the parameters for individual cities. The conditional mean estimates and confidence intervals shown in Figure 2 provide a better idea of how estimated effects differ among cities. Greene (2007) points out that since the conditional distributions are unknown, the actual ranges might be somewhat wider or narrower; however, for most distributions they should be a good approximations of the 95% confidence intervals.

As Figure 2 illustrates, population density was negatively associated with car trip frequencies and positively associated with transit trip frequencies. The effect of population density on car trip frequency was highly heterogeneous with considerable variations among cities. Not so in the case of transit trip frequency where all confidence intervals hover around the same ranges. In a similar manner, the effect of number of cars was heterogeneous for all modes, with a positive association with car trips, and negative associations with other modes.

Concerning the effect of preferred modal access when deciding current residential location, car access preference was positively associated with car trip frequency and negatively associated with other modes. The effect was heterogeneous for both car and non-motorized modes. Transit access preference was positively associated with non-car modes, being heterogeneous for transit trips. Contrary to our expectations, in the case of preferences, the difference in effects across cities were rather small.

[8] Note that for the triangular distribution defined earlier, the scale parameter equals the absolute value of the estimated coefficient. (see Greene (2005))

It is important to note that the assumed distribution of the random terms is rather arbitrarily defined, and results might be sensitive to different specifications, especially if the distribution spread is constrained.

Table 4. **Random parameter model estimation results**

	Car trip models				Transit trip models				Non-motorized trip models			
	B.E. Model		**Full Model**		**B.E. Model**		**Full Model**		**B.E. Model**		**Full Model**	
Number of observations	7408		7408		7408		7408		7408		7408	
Number of groups	57		57		57		57		57		57	
Log-likelihood (Constant)	-9038.57		-9038.57		-2145.03		-2145.03		-5855.111		-5855.111	
Log-likelihood (Random)	-8471.35		-8453.98		-1887.74		-1874.22		-5162.1		-5098.17	
σ^2 = LL(β)-LL(C)	0.063		0.065		0.120		0.126		0.118		0.129	
Base model Deviance R^2	0.028		0.028		0.104		0.104		0.148		0.148	
Deviance R^2	0.038		0.039		0.169		0.208		0.197		0.220	
Variables	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Constant	-0.216	-7.595	-0.219	-7.595	-0.975	-9.858	-0.929	-9.199	-0.406	-9.358	-0.435	-9.497
Individual and household attributes												
Age	0.004	3.686	0.003	3.016	-	-	-	-	0.004	3.696	0.003	2.666
Male	-0.184	-4.232	-0.182	-4.183	-0.437	-4.533	-0.417	-4.213	-0.362	-7.081	-0.335	-6.062
Worker	-0.252	-7.909	-0.258	-7.999	-0.288	-3.102	-0.292	-3.003	-0.840	-16.357	-0.823	-15.886
Number of cars in household	0.025	5.673	0.023	5.135	-0.155	-5.959	-0.136	-5.225	-0.093	-8.217	-0.078	-6.674
Driver's license	0.950	20.085	0.923	18.131	-0.254	-2.115	-0.251	-2.052	-	-	-	-
Number of bicycles in household	-	-	-	-	-	-	-	-	0.176	10.165	0.164	9.124
Nuclear household	0.226	7.253	0.212	6.097	-0.469	-3.802	-0.471	-3.772	-	-	-	-
Single household	-0.263	-3.863	-0.269	-3.765	-	-	-	-	0.151	1.936	0.168	2.134
Couple household (Under 65 years)	0.126	3.221	0.103	2.611	-	-	-	-	0.107	1.878	0.110	1.912
Built environment characteristics												
Log of population density	-0.018	-6.581	-0.017	-5.875	0.040	4.486	0.023	2.644	-	-	-	-
Log of commerce density	-	-	-	-	-	-	-	-	0.105	8.820	0.075	5.482
Train station within 800m	-0.081	-2.615	-0.074	-2.305	0.202	2.489	0.152	1.866	0.137	3.005	0.101	2.245
Residential access preference												
Car access preference	-	-	0.051	3.078	-	-	-0.248	-2.513	-	-	-0.084	-3.918
Transit access preference	-	-	-	-	-	-	0.174	3.573	-	-	0.109	2.196
Non-motorized access preference	-	-	-0.080	-2.627	-	-	-	-	-	-	0.415	5.926
Dispersion parameter												
α									2.860	8.682	3.350	7.148

Random parameters based highlighted in blue

Triangular distribution is used for random parameters. Scale parameter equals the absolute value of the mean.

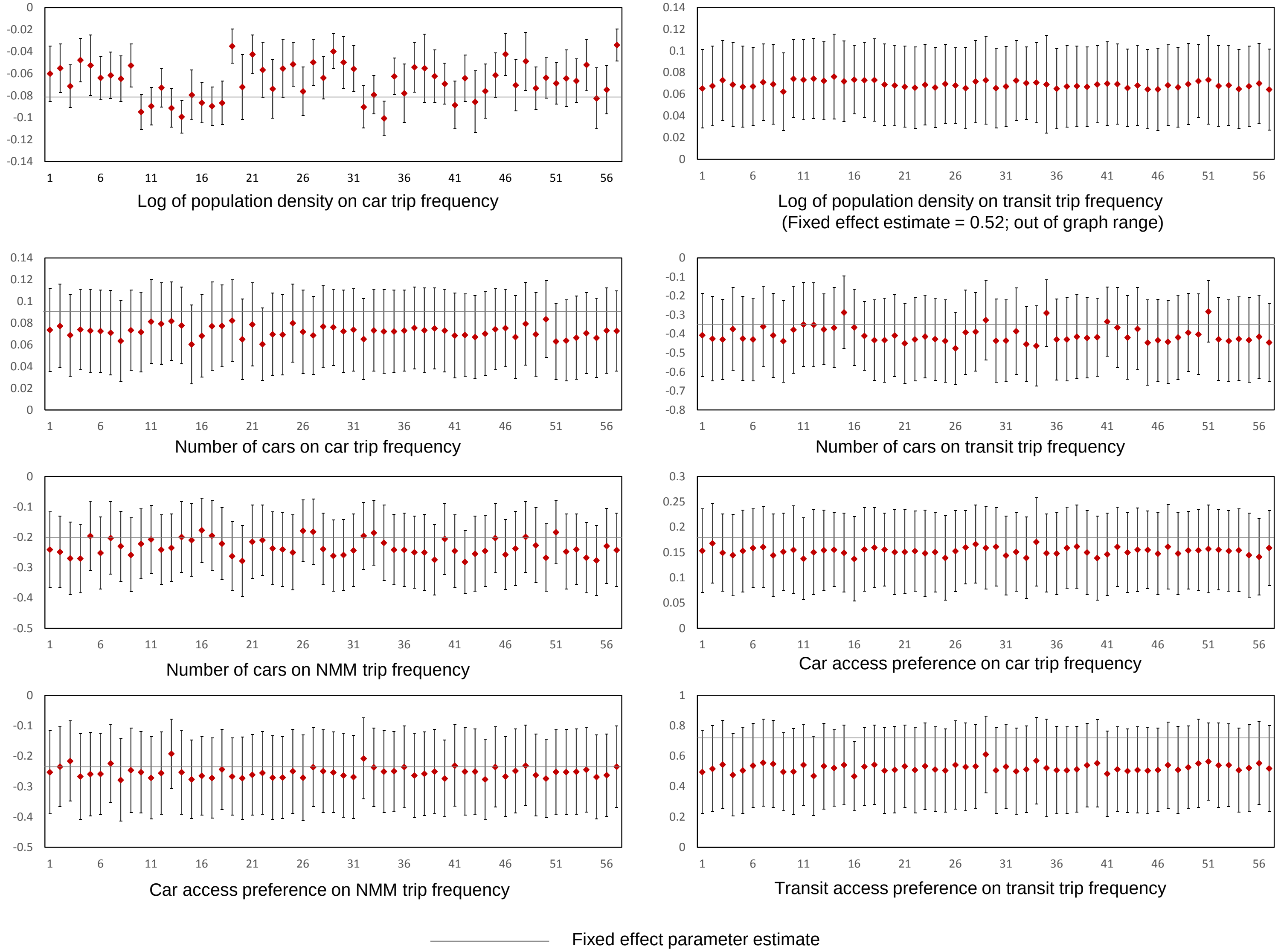

Figure 2. *95% Confidence intervals of estimated random parameters for full models*

Regarding the overall explanatory power of the models, as Table 5 illustrates, compared to the fixed parameter models, random parameter models resulted in better fit models, as measured by the likelihood ratio tests. For car trip frequency, although deviance R^2 was very low, socio-demographics explained the larger share of the variation in the data, while for transit trips, the combined explanatory power of built environment and preference variables was roughly the same to socio-demographics. In terms of non-motorized trips socio-demographics explained the largest share of the variation, but the inclusion of built environment and preferences variables resulted in considerable improvements in explanatory power.

Although direct comparisons with other studies are difficult due to differences in modelling approaches and reported statistics, an informal comparison was made with similar studies in the non-work trip frequency literature. As shown in Table 5, coefficients of determination seem to be in line with reported statistics in the literature.

Table 5. Coefficients of determination for this study and other studies in the literature

This Study [Dev. R^2]	Car Trips			Transit trips			Non-motorized trips		
Model	S.D.	B.E.	Full	S.D.	B.E.	Full	S.D.	B.E.	Full
Fixed parameter	0.028	0.030	0.032	0.104	0.145	0.160	0.148	0.176	0.185
Random parameter	-	0.038	0.039	-	0.169	0.208	-	0.197	0.220
LR X^2		3527.7	3515.0		126.7	100.9		46.1	62.5
d.f.		(3)***	(4)***		(3)***	(4)***		(2)***	(3)***
Other Studies [Model – Reported measure]									
Khattak & Rodriguez, (2005) [Negbin – ρ^2]			0.05			-			0.02
Cao, et al., (2006)[1] [Poisson/Negbin – Dev.R^2]			-			-	0.13 (Stroll); 0.38 (Shop)		
Cao et al. (2009b) [SURE – Adjusted R^2]			0.09			0.15			0.47

***Significant at the 0.01 level
[1] Only walking trips were considered
For other studies in the literature, only the best fit model statistics are reported

5. Discussion and conclusions

Estimated results suggest significant statistical associations between the built environment and non-work trip frequency. Consistent with findings in the literature higher population density was associated with lower car trip frequencies and higher frequencies by transit (e.g. Leck, 2006). Although population density was not statistically significant, commercial density was positively associated with non-motorized trips. Finally, access to transit service was associated with less car trips and more trips by alternative modes.

Although measurements of preference differ among studies, empirical results presented here are consistent with findings in the literature regarding the effect of preferences on non-work travel. In line with findings by Cao et al (2009b) significant positive associations were found between (i) car-related preferences and car travel, and (ii) transit and non-motorized modes preference on walking and biking trips. However in terms of explanatory power, model improvements from preference variables were somewhat modest, particularly for car trip models. As Chatman (2009) argued, the inclusion of modal access preference variables in the models only changed the built environment coefficients slightly but did not render them insignificant in any case.

That being said, data limitations did not allow for more comprehensive analysis of attitudes and preferences, but it is likely that the use of analysis tools like principal component analysis or factor analysis might help capture attitudes and preferences in a more adequate manner. At any rate, even with these methodologies, uncertainties remain in terms of how effective the control variables used account for latent preferences. Although a great deal of studies in the literature include some measure of attitudes and preferences as control variables, there is no overarching theory guiding the definition and measurement of attitudes (Bohte, et al., 2009); furthermore, the extent to which the rather diverse set of existing measures actually capture the self-selection effect remains undefined.

It is also important to note that only the direct effect of preferences on non-work travel was modeled. The indirect effect, that is, the effect of preferences on residential location that in turn affects travel behavior was not modeled in this analysis. In that sense, more complex models such as Structural Equation Models (SEM) might help overcome this limitation, as it becomes possible to specify both direct and indirect effects (see Golob (2003) for an overview of SEM in transport, and Cao et al (2007) and Scheiner (2010) for applications to the self-selection problem).

To conclude, controlling for residential self-selection hinges on stronger conditions than the ones established in this study, and is thus out of scope. Nevertheless, in spite of the limitations discussed, this study contributes to the existing body of literature by examining the role of the built environment and individual preferences on travel behaviour in the context of Japanese cities. In addition, this study highlights the importance of accounting for existing heterogeneity in the effects of car ownership, built environment characteristics and preference factors on travel behaviour. In particular, the effect of population density on car trip frequency was highly heterogeneous. In the present analysis heterogeneity is assumed to be a result of variations among city characteristics; nevertheless, further studies should also consider other sources of heterogeneity as well.

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