A Panel Data Approach to Understanding the Effect of the Built Environment on
Travel Behavior
- A Case Study of the Kashiwanoha Area, Chiba, Japan –

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In recent years, the concept of compact cities has permeated the sustainability discourse under the premise that compact high density developments can effectively reduce car use levels and promote use of alternative modes such as transit and non-motorized means. However, these arguments hinge on the existence of a true causal mechanism between built environment and travel behavior. Using panel data from a survey on new movers to a high density mixed use development in the Kashiwanoha area, Chiba prefecture, several models are estimated to test the effect of changes in the built environment on activity frequency by mode. Findings suggest that even after controlling for residential self-selection, the built environment exerts a significant effect on activity frequency for some activity types such as shopping and eating-out conditional on travel modes. Mode substitution effects were observed between frequencies of nearby activities reached by non-motorized means and faraway activities reached by car given changes in accessibility levels around home location. Asymmetric effects of changes in car ownership on activity frequency were also identified. Findings provide a good insight on the potential effects of retrofitting low density suburban areas through densification and land use mixes, an issue of critical importance in the context of rapidly ageing and depopulating cities and regions in Japan.

Keywords: *Travel behavior, Built environment, Residential self-selection, Panel data, Fixed effect model*

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1. Introduction

The compact city concept has become in recent years a paradigm for sustainable cities under the premise that high population density and mixed land uses might significantly reduce car use levels, and promote the use of transit and no-motorized modes (NMM), thus improving the livability of the city and the health of its inhabitants; in the particular context of Japan, compact cities are also viewed as a countermeasure to depopulation and ageing. However, these arguments hinge on the existence of a true causal mechanism between the built environment and travel behavior. Although a considerable body of literature has so far established significant statistical associations, the inference of a causal effect of the built environment and travel behavior relies on the elimination of all potential sources of bias, particularly, self-selection bias; that is, the bias stemmed from households self-selecting themselves into neighborhoods that meet their transport preferences. Using a panel data approach, this study aims at shedding some light on this causal relationship, using as a case study the Kashiwanoha area, in Chiba prefecture, Japan.

The rest of this paper is structured as follows. Section 2 briefly discusses the current state of affairs in the literature regarding built environment and travel behavior research. Section 3 describes the study characteristics and the data gathering methodology. Section 4 details the model structure, variables and its descriptive statistics. Section 5 presents the estimation results, followed by discussion of findings and implications in Section 6; finally, Section 7 wraps up the main conclusions of the study.

2. The built environment and travel behavior: findings from the literature

The built environment-travel behavior relationship has been the object of interest of a considerable number of studies in the past twenty years. As concepts such as Smart Growth, Compact Cities and New Urbanism permeate the sustainability discourse, researchers have tried to validate the existence the causal mechanism that would support the hypotheses put forth by high density and mixed use advocates. Certainly, as an indicator of intensity of land use, population density has been consistently associated with lower levels of car use and consequently higher levels of transit and non-motorized modes use^{1,2,3}). However, although a great number of studies have established significant statistical associations, establishing a causal relationship hinges on stronger conditions, that are sometime difficult to meet outside ideal experimental conditions. Mokhtarian & Cao⁴) suggested three conditions to be met in order to establish a causal relationship between the built environment and travel behavior: The existence of a statistically significant association, the non-spuriousness of this association, and the time precedence of the effect of interest.

The first two conditions can be reduced to the elimination of all possible sources of bias from the estimation. Although there are many sources of potential bias, of particular importance to the built environment-travel behavior studies is the residential self-selection bias, where households self-select themselves into neighborhoods that meet their travel preferences, making the built environment variables endogenous to travel behavior. Failure to control for self-selection thus results in biased and inconsistent estimators of the effect of the built environment on travel behavior.

The third condition refers to discarding the possibility of reverse causality in the variables of interest; in this case, to validate that changes in the built environment in fact cause changes in travel behavior and not the other way around.

Methodologically, there are several approaches to address these issues. Due to space constraints,

only a summary of methodological approaches⁽¹⁾ and main findings are presented here, both from a cross-section and a longitudinal perspective.

2.1. Cross-sectional approach

From a cross-sectional perspective, there are several ways to address the self-selection problem, this section will discuss the most commonly used approaches, namely statistical control models, instrumental variables, sample selection and propensity score models, discrete choice models and finally structural equation models (SEM).

To control for self selection, it is reasonable to think of the residential self-selection bias as a form of omitted variable bias. In that sense, by taking 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. After regressing trip frequency and trip ratio by mode on built environment variables, and further incorporating travel attitudes, personality and lifestyle factors, Kitamura et al.⁽⁵⁾ were among the first ones to question the real magnitude of the built environment effect on travel behavior. They found that including individual attitudes and preferences in the model reduced the estimated magnitude of the effect of land use on trip frequency and ratio; furthermore, individual attitudes and preferences explained a higher proportion of the variation in the data. The implication here is that individual attitudes partially explain the observed built environment attributes; attitudinal variables are therefore thought as possible controls for residential self-selection, thus its inclusion might mitigate selection bias.

Chatman⁽⁶⁾ suggested that if well self-selection might reduce the magnitude of the built environment effect, it does not render it insignificant. The built environment effect has also been found to be particularly strong for non-motorized trips, with evidence of mode substitution between car and non-motorized modes given different land use mix levels^(7,8). Naess⁽⁹⁾ also found significant effects on traveled distances by car, but argued that the extent to which people choose their residential location based on transport considerations might be limited.

In the particular case of Japan, to the best of our knowledge, the literature is rather scarce. A study by Parady et al.⁽¹⁰⁾ on travel behavior in the Kanto Region, found that after controlling for preference for modal access at the time of the last move, higher land use mix levels and closeness to transit stations were positively associated with non-work transit and non-motorized trip frequency.

The second approach to control for self-selection involves purging the built environment variables of its correlation with travel behavior through instrumental variables; nevertheless, finding a suitable instrument, that is, an instrument that is correlated with the built environment but at the same time exogenous to travel behavior, might be a challenging task. In the context of American or European cities, considering that urban areas developed before the second world war were more compact and mixed use, the percentage of buildings built before 1940s and 1960s were used as instruments for the built environment^(11, 12); findings however, were different among studies, with Boarnet and Sarmiento⁽¹¹⁾ finding no significant effects in most models and a high sensitivity to model specification. Furthermore, these instruments are very location specific and in the particular case of Japan, unfeasible given differences in its urban development patterns. Khattak and Rodriguez⁽¹³⁾ used non-transport related residential preferences as instruments for type of neighborhood and found that households in neo-traditional neighborhoods⁽²⁾ exhibit similar number of overall trips but fewer car trips and shorter travel distances.

The third approach considers the self-selection problem in a program evaluation framework. In that sense, the built environment is considered as the treatment of interest. Given the non-random allocation of treatment (Households choose residential location by themselves) the first step is to estimate the probability of choosing a specific type of neighborhood given a set of covariates.

The Heckman Sample Selection model (or Heckit model) assumes a binary treatment, and estimates treatment probability using a binary probit or logit model. The second step consists on estimating the regression of interest and introducing a sample selection correction coefficient to correct for selectivity bias. Zhou and Kockelman¹⁴⁾ and Cao¹⁵⁾ estimated Heckit models for vehicle kilometers traveled (VKT), where the sample selection model was a binary probit of neighborhood type (urban vs. suburban). Both models estimated significant differences in traveled distances and attributed the largest share of the effect on built environment characteristics.

Similar to the sample selection models, propensity score matching consists on estimating the probability of treatment given a set of covariates; treated and untreated individuals are then matched on the estimated propensity and the differences in outcomes are compared. Alternatively, the sample can be stratified given the estimated propensity score and difference in outcomes for sub-groups estimated. Using propensity score matching for different treatments (i.e. urban vs. suburban, exurban vs. urban etc.), Cao et al.¹⁶⁾ found a positive association between VKT and distance from the city center. Regarding walking trips, Boer et al.¹⁷⁾ found through propensity score stratification that higher level of business diversity were associated with more walking.

While Cao¹⁸⁾ suggests that propensity score methods might mitigate selection bias up to 90% but not fully eliminate it, it is important to note that both sample selection and propensity score models are as good as its selection probability model; in that sense, poorly fitted probability models results in poor estimates of the average treatment effect of interest.

From a discrete choice modeling approach, residential location and mode choice are considered as an interdependent decision, thus modeled jointly. After controlling for self-selection, significant effects of accessibility, land use mix and density on commuting mode choice have been identified^{19, 20)}, more complex model have also jointly modeled the residential location, car ownership and commute mode choice, assuming car ownership as endogenous to travel behavior as well²¹⁾. Most studies in the literature however, perhaps due to modeling complexities focused on commuting mode choice only, and have not yet considered other types of activities.

Finally, Structural Equation Models have also been used to address the self-selection issue as endogeneity of variables is allowed. A study by Bagley & Mokhtarian²²⁾ on distance traveled using SEM found a very small effect of residential location characteristics on travel behavior when controlling for attitudes and lifestyle preference, which had a larger effect on travel. Scheiner and Holz-Rau²³⁾ on the other hand analyzed share of trips by mode and traveled distances found that life situation has a stronger effect than lifestyle on behavior, but argued that the effect of lifestyle might be rather indirect by influencing location preferences and residential location choice. Segmenting activities by type, Scheiner²⁴⁾ further suggested that the built environment had little effect on job and leisure distances, but was the most influencing factor on maintenance tasks.

In general, cross-sectional data has the advantage of being highly available, but it comes at a cost; since data is observed at only one point in time, the estimation of a causal relationship hinges on very strong conditions that are in many cases difficult to meet given available data, especially in the absence of randomized data. Nevertheless, the approaches discussed above provide some alternatives to at the very least mitigate self-selection bias.

2.2. Quasi-longitudinal and longitudinal approach

Quasi-longitudinal and longitudinal methods not only allow to control for residential self-selection but also to establish the direction of the effect of interest; furthermore, true panel data studies allows the researcher to observe the outcome travel behavior given changes in the built environment characteristics, so they can be understood as natural experiments.

Quasi-longitudinal studies consist on gathering information of past behavior retrospectively in the absence of true panel studies. Handy et al.²⁵⁾ provides a good example of the advantages of these studies. Using the same dataset, a cross section analysis of vehicles kilometers traveled found no significant associations of VKT with built environment features once attitudes were accounted for. On the other hand, a quasi-longitudinal approach on changes in driving levels found significant effect in changes in accessibility perception in explaining change in driving levels.

Quasi-longitudinal SEM studies of changes in travel mode use levels have suggested significant effects of changes in built environment characteristics as a result of residential relocation on changes in mode use, where suburban relocation is associated with higher driving levels and less transit and non-motorized travel, an effect opposite to the one observed after urban relocation²⁶⁾, a finding similar to Cao et al.²⁷⁾ who found reduced driving levels and increased walking given relocation to neo-traditional neighborhoods. Handy et al.²⁸⁾ also found significant changes in walking levels given changes in accessibility perception but suggested that attitudes play a larger role in explaining changes in bicycle use levels.

Although quasi-longitudinal data helps bridge some of the limitations of cross-sectional data, it is not without limitations, especially regarding the reliability of retrospective data, as respondents might forget past behavior, or their responses might be influenced by most recent behaviors.

Among all methodologies reviewed so far, true panel data studies provide the best conditions to understand the true effect of built environment on travel behavior, as they approximate as much as possible an ideal experimental situation. Nevertheless, this comes at an increase in execution costs, and considerably more hardships in keeping track of the sample at different points in time. At any rate, true panel data studies remain conspicuously few in the literature. A fixed effect model on walking by Wells and Yang²⁹⁾ found that moving to places with fewer cul-de-sacs was associated with an average increase in walking. Incidentally, the study also found an expected decrease in walking levels given an increase in the number of service jobs per resident; nevertheless it is important to note that the study was conducted with a very small sample size of 32 consisting mostly of low-income African-American women. Although not directly related to transportation per se, a first difference regression of changes in body mass index (BMI) on changes in land use mix and sprawl levels found no significant effect of the built environment³⁰⁾, the implication being that built environment characteristics do not increase the likelihood of a more active lifestyle as a result of more walking and physical activity within the neighborhood, and that people with tendency to sedentary lifestyles tend to self-select themselves into more suburban areas. Finally, Krizek³¹⁾ estimated an OLS regression using first differenced dependent variables of traveled distances, number of tours and trips per tour on changes in neighborhood and regional accessibility and found that households moving to areas with higher neighborhood accessibility reduce on average the number of vehicle kilometers driven and overall person kilometers traveled.

3. Methodology and Study Characteristics

In order to overcome some of the limitations of cross-sectional analysis previously discussed, and to contribute to the existing body of literature in an area where it is currently lacking, this study addresses the built environment and travel behavior relationship from a panel data perspective. Specifically, the principal object of interest is to understand how changes in the land use characteristics around home location affect activity frequency by mode. This motivates the following hypotheses:

1. A positive change in the number of potential opportunities for any given activity within one's neighborhood increases the average frequency that such activity is conducted nearby and reached via non-motorized modes such as walking or biking.
2. A positive change in the number of potential opportunities for any given activity within one's neighborhood decreases the average frequency that such activity is conducted faraway and reached by car.

In other words, we hypothesize that there exists a mode substitution mechanism between private vehicle and non-motorized modes given an increase in accessibility to any given activity around home location.

To test these hypotheses, data from a panel data survey conducted by The University of Tokyo between autumn 2007 and autumn 2008 on relocating households were used. The survey was conducted on households that purchased new apartments in the Park City Kashiwanoha Campus Project, located in the Kashiwanoha area of Kashiwa city, Chiba prefecture, at roughly 30 Kilometers from Tokyo. The area is connected to Tokyo via the Tsukuba Express railway line (see Figure 1).

Figure 1. Location of the Park City Kashiwanoha Campus and Previous Location of Households

As of 2012, the Kashiwanoha area exhibited a population of 3,277 inhabitants with a population density of 1,731 persons per km² (Roughly half of the density Kashiwa city, and approximately one eighth of the density of the 23 special wards of the Tokyo Metropolitan Area)^{32,33}

Against this suburban background, the Park City Kashiwanoha Campus Project –which

constitutes the target area of this study— is a high-density, mixed use project under development around the Kashiwanoha Campus station which contemplates commercial, institutional and residential facilities. The project is part of an ambitious master plan –with a planned population of 26,000– that seeks to create an environmentally sustainable town that fosters a healthy lifestyle, and serves as a knowledge hub for academia and industry³⁴). At the time of the survey execution, the shopping center adjacent to the station had already open, roughly a five minute walk from the target residential buildings. Facilities nearby the Kashiwanoha Campus station area include two university campuses, several research institutes, as well as abundant green open spaces and sport facilities.

The survey consisted on a three tier self-administered, mail-back, paper-based questionnaire, targeting all households that purchased apartments in the Park City Kashiwanoha Campus Project. The survey instrument consisted of two questionnaires, a household questionnaire to be answered by the member of the household who decided the relocation to Kashiwanoha, and an individual questionnaire to be answered by all household members over elementary school age.

In Tier 1, conducted six months before the moving process started on August 2007, information was gathered on household characteristics, individual travel behavior and lifestyle before moving. In Tier 2, conducted on December 2007, information was gathered on future travel behavior intention given information provided by the researchers about the amenities and facilities available around the new neighborhood. Finally, in Tier 3, conducted five months after the moving process started on August 2008, information was gathered on household characteristics, individual travel behavior and lifestyle after moving. Since the main objective of this study is to analyze the effects of changes in the built environment on travel behavior, only data from Tier 1 and Tier 3 were used for the analysis. Given the existence of systematic inconsistencies between behavioral intention and actual behavior³⁵), Tier 2 data, which documents behavior intention after moving, were excluded from the analysis.

Of the total 300 households targeted, the effective sample size in the period before moving to Kashiwa was of 132 individuals from 80 households; however, the effective sample size in the post-moving period was of 98 from 49 households.

Regarding the effective panel sample used in the analysis, that is, the sample that did not attrite; the average household size was 2.73, with an average of 2.20 adults and 1.51 workers in the household. Almost 50% of the sample possess a driver's license and 78.5% of households own at least one car. Regarding bicycle ownership, the sample mean is 1.55, with 80.6% of households owning at least one bicycle. General socio-demographic characteristics of the effective final sample are presented in table 1.

Table 1. General socio-demographics characteristics of the sample (after moving)

Variable Name	Mean	Std.Dev.	Minimum	Maximum	N
Age	39.79	13.67	14.00	77.00	98
Household size	2.73	0.88	1.00	5.00	49
Male	0.47	0.50	.00	1.00	98
Driver's license	0.49	0.50	.00	1.00	98
Number of adults in household	2.20	0.54	1.00	4.00	49
Number of workers in household	1.51	0.77	.00	4.00	49
Number of cars in household	0.92	0.34	.00	2.00	49
Number of bicycles in household	1.55	1.17	.00	6.00	49

Regarding pre-moving residential location of households (see Figure 1), 56% of the households

moved in from within Chiba prefecture, followed by 29% moving from the Tokyo Metropolitan Area, the rest of the households moved from other prefectures in the Kanto Region like Ibaraki prefecture (8%), Kanagawa prefecture (4%) and Saitama prefecture (2%).

4. Model Structure and Variable Description

4.1. Model Specification

Given the described study characteristics, the analysis can be thought of in terms of a natural experiment, where residential relocation provides the change in the explanatory variables of interest; however, since households themselves choose where to relocate, the residential location is not a random process, thus, if the residential location choice is related to the outcome variables, then estimation results are biased and inconsistent due to self-selection.

Regarding residential self-selection, the main assumption is that the factors that account for residential self-selection and car ownership⁽³⁾, be it attitudes, preferences or lifestyle factors, are part of the unobserved individual heterogeneity, and are assumed constant during relatively short periods of time (i.e. the survey period). The main rationale behind this assumption is that due to the repetitive nature of travel, habits play an important role in shaping attitudes and thus attitudes and preference might be slow to change. Furthermore, if there was in fact an attitude or preference change spurring the change in residential location, it is assumed to have happened before the survey period started, that is, before the relocation choice was made, hence attitudes remained fixed after relocation.

Under this assumption, a fixed effect model is proposed to control for self-selection bias. Although a brief explanation of the fixed effect models is presented below, interested readers are referred to Wooldridge⁽³⁶⁾, where this next section draws heavily from.

The fixed effect model is a type of unobserved effect model (UEM) of the form:

$$y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it} \quad (1)$$

Where α is the unobserved individual heterogeneity, or individual fixed effect. Given equation (1) then the usual strict exogeneity assumption must also be conditioned on α_i :

$$E(\varepsilon_{it} | x_{it}, \alpha_i) = 0 \quad (2)$$

The assumption that the individual fixed effect is uncorrelated with the idiosyncratic error ε , allows the unbiased and consistent estimation of the effects of interest given individual heterogeneity. Now, in order to properly estimate the coefficients of interest, it is necessary to weed out the fixed effect α .

In the context of this analysis, let t_0 be the time period before moving, and t_1 be the time period after moving. Given model equations at t_1 and t_0 for the i_{th} individual respectively:

$$y_{i1} = \alpha_i + \beta x_{i1} + \gamma z_{i1} + \varepsilon_{i1} \quad (3)$$

$$y_{i0} = \alpha_i + \beta x_{i0} + \gamma z_{i0} + \varepsilon_{i0} \quad (4)$$

Where y_i is the travel behavior variable of interest, x_i is a vector of time changing individual and household characteristics, z_i is a vector of time changing built environment characteristics, and ε is the idiosyncratic error term. By taking the deviation from mean at each time t , we then get a time demeaned equation for the i_{th} individual:

$$y_t - \bar{y} = \alpha - \bar{\alpha} + \beta(x_t - \bar{x}) + \gamma(z_t - \bar{z}) + \varepsilon_t - \bar{\varepsilon} \quad (5)$$

Where the i notation is suppressed for simplification purposes. Since the fixed effect α is constant in time, it is easy to see how it cancels out in equation (5); thus, for estimation purposes, the fixed effect model is just a pooled OLS regression of the time demeaned equation (5). Another way to

estimate the fixed effect model is via the so-called dummy variable regression, where instead of equation (5) a pooled OLS regression of equations (3) and (4) is ran including one dummy variable for each individual i . This approach yields the exact same results for β and γ as the time demeaned pooled OLS regression, and also provides an estimate of the individual fixed effect α for each individual i .

The main drawback of using the fixed effect model is that given the nature of equation (5), time invariant explanatory variables cannot be introduced in the model as they will be swept away with the fixed effect α . This translates in reduced variability in the data, and consequent larger standard errors and lower R^2 values. Nevertheless, since we are interested in unbiased and consistent estimators of the effects of the built environment, which is time variant, the model adequately fits to the needs of this study. Furthermore, fixed effect models have also been shown to be more robust to attrition bias than random effect models³⁷⁾, an issue present in most practical applications of panel data studies.

4.2. Dependent Variables

To gather information on activity frequency, our outcome variable of interest, respondents were asked to indicate the number of times they engaged in four different types of activities, the frequency these activities were conducted nearby and/or faraway, and the transport mode used on each case. The questionnaire was formulated in such a way that respondents could specify for both nearby and faraway activities, total frequency by activity type, and further specify how many times these activities were conducted by each transport mode. The time period could also be defined by the respondent as weekly, monthly or yearly, thus allowing for specification of very low frequency activities.

The four activity types considered were leisure, shopping, educational training, and eating-out. Leisure activities include going to the movies, walks, exercising, etc. Shopping refer to both discretionary and non-discretionary shopping. Educational training consists of all educational activities excluding formal training in high schools and universities, while eating-out activities refers to all eating and drinking out activities such as going to a restaurant, diner, bar, etc.

Nearby activities are defined as those activities that can be reached within 20 minutes in non-motorized modes; all activities outside that range are considered activities faraway. Finally, modes were classified as private vehicle, transit and non-motorized means (NMM).

Given all potential outcomes, paired sample t-tests were conducted to evaluate which changes in behavior are statistically different between time periods (result highlights are summarized in Table 2). Regarding activity types, no outcome combination related to leisure activities was statistically different from zero. This might suggest that individuals have a rather fixed time budget allocated irrespective of residential location. Furthermore, leisure activities might depend more on factors such as lifestyle, than built environment characteristics at home location²⁴⁾. Another important factor might be the rather disparate aggregation of leisure activities under the leisure category. In that sense, it is likely that a more disaggregate classification might yield different results.

On average, total activity frequency increased by 8% (p value = 0.085), as compared to pre-moving levels. At the same time, there was a significant increase in nearby activity frequency of 21%, and a reduction of faraway activities of 20%. A similar pattern is observed when segmenting activity frequency by mode. Total number of activities reached by car exhibited a 41% reduction in frequency, while activities reached by non-motorized modes such as walking and biking increased by 39%.

Table 2. Paired sample t-test of changes in activity frequency (result highlights)

Variable Name	Mean at t ₀	Mean of diff.	% mean change	S.D. of diff.	S.E. mean	t-stat	d.f.
Total activity frequency	371.48	31.43	8%	176.28	18.09	1.74	94
Total activity frequency Nearby	250.11	51.52	21%	157.86	16.11	3.20	95
Total activity frequency Faraway	121.37	-23.84	-20%	93.23	9.47	-2.52	96
Total shopping frequency	161.23	32.92	20%	102.14	10.32	3.19	97
Total education frequency	15.09	-6.74	-45%	30.63	3.09	-2.18	97
Total eating-out frequency	44.82	-0.87	-1%	60.16	6.10	-0.14	96
Total leisure frequency	80.05	2.20	3%	111.27	11.30	0.19	96
<i>Changes in activity frequency given travel mode</i>							
Total activities by car	73.30	-30.02	-41%	87.89	9.26	-3.24	89
Total activities by transit	45.93	-2.90	-6%	96.99	10.22	-1.94	89
Total activities by NMM	143.42	56.50	39%	171.14	18.04	3.13	89
Total leisure by car Faraway	10.03	-4.26	-42%	25.96	2.63	-1.61	96
Total leisure by transit Faraway	9.40	4.21	45%	34.92	3.55	1.19	96
Total leisure by NMM Nearby	50.20	-0.01	0%	94.14	9.66	-0.00	94
Total shopping by car Faraway	15.80	-6.87	-43%	29.83	3.01	-2.28	97
Total shopping by transit Faraway	9.85	0.93	9%	33.75	3.40	2.72	97
Total shopping by NMM Nearby	57.32	47.02	82%	93.61	9.66	4.87	93
Total education by car Faraway	2.63	-0.30	-11%	10.20	1.03	-0.29	97
Total education by transit Faraway	4.27	1.77	41%	30.61	3.09	0.57	97
Total education by NMM Nearby	10.54	-4.54	-43%	28.32	2.88	1.57	96
Total eating-out by car Faraway	7.98	-6.44	-81%	17.96	1.82	-3.53	96
Total eating-out by transit Faraway	8.63	-6.65	-77%	21.34	2.16	-3.06	96
Total eating-out by NMM Nearby	16.27	16.41	101%	47.16	4.86	3.37	93

*All other activity frequencies (given mode and distance) not presented here were not significant.

Total shopping frequency increased by 20%, an increase largely attributed to an 82% of nearby non-motorized shopping; conversely, average faraway shopping frequency by car was reduced by 43%. Change in overall eating-out frequency was not statistically different from zero, however, there was a significant reduction of 81% of total faraway eating-out frequency; on the contrary, average nearby eating-out frequency by non-motorized modes increased by twofold. Changes in activities reached by transit were not statistically different from zero, but there was a statistically significant change in faraway eating-out frequency by transit, with an average increase of 77%. Finally, average educational activity frequency was reduced by 45%; however, when segmenting by travel mode or location of the activity differences were not statistically significant.

Given the stated hypotheses, hereinafter, the focus of the analysis will be limited to those variables segmented by travel mode, as the primary purpose of the study is explore changes in travel behavior.

4.3. Independent Variables

As described in the model specification, explanatory variables consist of time variant individual and household variables and built environment variables. Among socio-demographics, time-changing variables includes household size, number of workers, commuting frequency, as well as number of and bicycles in the household. Change in number of cars in the household range from

-1 to +1, with 12.2% of the households reducing one unit, and an equal proportion increasing one unit. Changes in number of bicycles range from -4 to +2, with 16.33% of the households reducing at least one bicycle and an equal percentage increasing at least one bicycle.

Regarding built environment variables, land use data for both pre-moving and post-moving periods were gathered using Supper Mapple Digital, a commercially available map software produced by Shobunsha Publishers, which contains detailed information about existing facilities classified according to type and released yearly. Older versions were purchased in order to match land use information to each time period.

Changes in number of facilities were evaluated at different radius from home location, 500 meters, 1 kilometer, and 2 kilometers. Facilities considered in the analysis include leisure⁽⁴⁾ and eating facilities, as well as grocery and non-grocery shopping facilities. On average, after moving to Kashiwa, a positive change in total number of facilities at 500 meters and 1 km is observed, that is, a mean increase of 17 and 4 facilities respectively; however, when evaluated at a 2 km radius, there is an average decrease of 20 facilities. At the 500 meters level, there is a positive change in the number of eating-out, leisure and non-grocery shopping facilities, and a negative, albeit small change in grocery shops. These changes in the built environment highlight the high density, compact and mixed use nature of the project that contrasts with its more suburban and low density surroundings. Regarding changes in distance to closest facilities, there is an average reduction of 1.2km to the closest rail station, with a maximum reduction of 8.4 km. Mean change in distance to other facilities such as convenience store, supermarkets, and eating-out facility are also negative, with average values of -231m, -352m and -235m respectively. An average increase to the closest park of 138m was also observed.

It is important to note that mean difference does not tells us much about the distribution of these changes; note the large increase in the size of the standard deviations with respect to the means, as the set radius increases, suggesting a rather spread out distribution of the change. Table 3 summarizes the explanatory variables as well as the average changes and standard deviations of changes after moving to Kashiwa⁽⁵⁾.

Table 3. Explanatory variables and average changes after moving

Variable Name	Mean at t ₀	Mean at t ₁	Mean of difference	Std. dev. of difference	Min. change	Max. change
Household size	2.33	2.73	0.40	0.61	0	2
Number of workers in household	1.24	1.51	0.26	0.49	0	2
Number of cars in household	0.95	0.93	-0.02	0.50	-1	1
Number of bicycles in household	1.67	1.59	-0.08	1.07	-4	2
Commuting frequency	3.68	3.11	-0.57	1.86	-6	5
All facilities in 0.5km radius	14.52	32	17.48	17.81	-50	32
All facilities in 1km radius	48.13	52	3.87	45.40	-182	51
All facilities in 2km radius	155.75	136	-19.75	134.53	-458	131
All shopping in 0.5km radius	8.32	14	5.68	9.85	-31	14
All shopping in 1km radius	29.83	19	-10.83	26.25	-111	18
All shopping in 2km radius	93.45	75	-18.45	75.68	-261	71
Eating facilities in 0.5km radius	5.56	16	10.44	7.85	-20	16
Eating facilities in 1km radius	16.40	31	14.60	17.98	-64	31
Eating facilities in 2km radius	52.85	48	-4.85	50.29	-182	48

Table 3. Explanatory variables and average changes after moving (Continued)

Grocery shops in 0.5km radius	4.65	4	-0.65	4.98	-15	4
Grocery shops in 1km radius	16.94	7	-9.94	16.18	-59	6
Grocery shops in 2km radius	57.52	28	-29.52	56.23	-212	24
Leisure facilities in 0.5km radius	0.64	2	1.36	1.33	-9	2
Leisure facilities in 1km radius	1.89	2	0.11	3.00	-18	2
Leisure facilities in 2km radius	9.45	13	3.55	18.13	-79	13
NG shopping in 0.5km radius	3.70	10	6.30	5.77	-16	10
NG shopping in 1km radius	12.89	12	-0.89	11.78	-52	12
NG shopping in 2km radius	35.93	47	11.07	23.39	-73	47
Leisure + NG shopping in 0.5km radius	4.33	12	7.67	6.25	-15	12
Leisure + NG shopping in 1km radius	14.78	14	-0.78	13.45	-59	14
Leisure + NG shopping in 2km radius	45.38	60	14.63	35.53	-95	59
Distance to closest station	1410.0	210	-1200	1340	-8400	100
Distance to closest convenience store	309.36	78	-231.36	180.29	-725	28
Distance to closest supermarket	581.02	229	-352.02	354.67	-1137	99
Distance to closest eating facility	404.40	169	-235.40	384.81	-2329	106
Distance to closest park	1581.3	1730	148.63	1490.39	-3270	1630
Distance to closest grocery shop	286.11	78	-208.11	165.68	-679	28

NG shopping: Non-grocery shopping. All distances given in meters.

5. Estimation Results

Given the hypotheses stated in Section 3, seven models are estimated using log-transformed variables as follows:

1. Log of yearly activity frequency by car
2. Log of yearly activity frequency by NMM
3. Log of yearly shopping frequency by car | Faraway
4. Log of yearly shopping frequency by NMM | Nearby
5. Log of yearly eating-out frequency by car | Faraway
6. Log of yearly eating-out frequency by transit | Faraway
7. Log of yearly eating-out frequency by NMM | Nearby

To evaluate the goodness of fit of the models, three types of F tests are presented. The first one is a joint significance test of fixed effects and regression fit (H_0 : No fixed effect or fit in regression). A second statistic is provided to test the goodness of fit of the regression model independent of fixed effects (H_0 : No fit in the regression of Y on explanatory variables); failure to reject the null hypothesis suggests that the explanatory variables fail to explain the observed outcomes; in that sense, a significant F statistic against the first null hypothesis, but an insignificant statistic against the second null hypothesis suggests that while individual heterogeneity explains changes in outcome, the explanatory variables do not. The third statistic tests whether there is in fact a fixed effect in the model; a failure to reject the null hypothesis thus favors a more parsimonious pooled OLS model over the fixed effect estimate.

All models are statistically significant against the first and second null hypotheses at least at the 5% level, suggesting that the explanatory variables significantly explain changes in outcome. In terms of the third test, for models 1-4 the null hypothesis is rejected at all levels of significance. Regarding the eating-out models (models 5-7), for the faraway eating-out by car model the null

hypothesis is rejected only at the 10% level, while for the remaining two models, the null hypothesis cannot be rejected at any level, hence in all cases, the pooled OLS results are presented instead.

Table 4 presents the estimation results of the overall activity frequency models by car and non-motorized modes. *Ceteris paribus*, reductions in distance to the nearest train station are associated with reductions in activity frequency by car and increases in activity frequency by non-motorized modes. The semi-elasticities⁽⁶⁾ of change in distance to nearest stations are estimated at 0.246 and -0.402 respectively; that is, a one kilometer decrease in distance to the nearest station translates into an average decrease of 24.6% of activity frequency by car and a consequent 40% increase in activities by non-motorized means. This suggests the existence of a mode substitution effect given reductions in distance to stations, an effect attributed to a larger concentration of activity opportunities around train stations.

The effect of a one car increase in the household translates in an average 207% increase in activity frequency by car; on the other hand, the effect of one car reduction in the household is not statistically different from zero. This phenomenon might be explained by an inertia effect in car use, where due to car use habit effects, a reduction of the number of cars in the households might lead to an increased use of the remaining unit(s) in order to compensate the lack of the disposed unit. Furthermore, this difference suggests that the effect of changes in car ownership on behavior is not linear, highlighting the importance of considering not only the change in the variables of interest but also the direction of that change. In terms of activity frequency by non-motorized means, there was no statistically significant effect of changes in car ownership, either increase or decrease.

The semi-elasticity of changes in the overall number of facilities in a 1km radius on activity frequency by car is estimated at -0.010, suggesting a 1.0% reduction in average activity frequency by car given a one unit increase in the number of facilities. On the other hand, positive changes in the number of eating-out and non-grocery shopping in a 500m radius was positively associated with activity frequency by non-motorized means, that is, an expected 2.2% increase in frequency given a one shop increase. The observed effects suggest that an increase in potential opportunities within walking and biking distance might in fact contribute to a reduction of car use and incentivize the use of non-motorized means.

As illustrated in Table 5, models 3 and 4 focus on faraway shopping frequency by car and nearby shopping frequency by NMM respectively. Change in distance to the nearest train station is not statistically different from zero in the NMM model; on the other hand, the effect on faraway car shopping was significant at the 5% level, with an estimated semi-elasticity of 0.269, suggesting an expected 26.9% reduction in car shopping frequency given a one kilometer reduction in distance to the station. Other accessibility measures such as change in number of retail shops in a 1km radius were not statistically significant.

A one car reduction in the household translates on an average 82.9% increase in nearby NMM shopping frequency, and an expected 77.2% reduction in faraway car shopping frequency. In terms of a one car increase, a similar magnitude, yet different direction effect was observed in the NMM model where a one car increase is associated with an expected 88.8% reduction in non-motorized shopping; however, this is not the case in the car shopping model, where the coefficient was not statistically different from zero. Interestingly enough, this relation is opposite to the one observed in model 1, where a car increase was associated with an increase in car use, implying

not only an asymmetry of the effect, but also differences in the nature of this asymmetry given activity type.

Table 4. Fixed effect model estimation results for overall activity frequency

Fixed Effect Model (robust)	Model 1: Log of yearly activity frequency by car		Model 2: Log of yearly activity frequency by NMM	
N	176		176	
No. of parameters	92		92	
Degrees of freedom	84		84	
SSR	175.97		168.99	
Standard error of e	1.45		1.42	
F test (prob) [dfr, dfur]	3.26(0.000)	[91,84]	2.42(0.000)	[91,84]
H0: No fixed effect or fit in regression				
F test (prob) [dfr, dfur]	7.05(0.000)	[4,171]	5.54(0.000)	[4,171]
H0: No fit in the regression				
F test (prob) [dfr, dfur]	2.79(0.000)	[87,84]	2.133(0.000)	[87,84]
H0: No fixed effect				
Log likelihood	-249.72		-242.44	
Restricted Log likelihood	-382.68		-359.50	
Chi-sq (prob) [df]	265.91(0.000)	[91]	226.69(0.000)	[91]
Variable	Coefficient	t stat	Coefficient	t stat
Change in distance to station (Km)	0.246 (0.066)	3.723	-0.402 (0.137)	-2.919
Car number reduction	-0.086 (0.273)	-0.313	0.327 (0.474)	0.690
Car number increase	2.075 (0.488)	4.250	-0.255 (0.390)	-0.654
Change in number of eating and non-grocery shopping facilities in a 0.5Km radius	- -	-	0.022 (0.010)	2.090
Change in overall number of facilities in a 1Km radius	-0.010 (0.003)	-3.084	- -	-
Classical model statistics test	Log-L	R²	Log-L	R²
1.Constant term only	-382.679	0.000	-359.503	0.000
2.Fixed effects only	-273.059	0.712	-272.840	0.626
3.Explanatory variables only	-369.230	0.142	-348.774	0.115
4.Explanatory variables and fixed effects	-249.722	0.779	-246.157	0.724

A one kilometer reduction in distance to the nearest grocery shop is associated with an average increase in NMM shopping frequency of 156%. In terms of grocery shopping, and assuming a fixed need for groceries given fixed household characteristics, a plausible explanation might be that individuals living closer to grocery shops increase their shopping frequency while at the same time reducing the volume of products purchased on each visit. That being said, the negative coefficient of the number of grocery stores in a 500m radius on NMM shopping suggests a decrease in shopping frequency given an increase in the number of shops. Although a rather counter-intuitive finding, it is important to note that the commercial floor area is not being taken into account. Furthermore, looking at the descriptive statistics presented in table 2 and 3, on average, the change in number of grocery shops after moving to Kashiwa decreased at any radius, while both shopping frequency and NMM nearby shopping frequency increased considerably. If well the overall number of shops at the 500m radius is on average lower, it is likely that facilities in the Kashiwanoha Campus Project, which was developed to cater a specific market segment,

match well with the resident's preferences as consumers, thus increasing shopping frequency even with less number of facilities around home.

Table 5. Fixed effect model estimation results for shopping frequency

Fixed Effect Model (robust)	Model 3: Log of yearly Car shopping frequency Faraway		Model 4: Log of yearly NMM shopping frequency Nearby	
N	192		184	
No. of parameters	101		97	
Df	91		86	
SSR	152.10		134.27	
Standard error of e	1.29		1.25	
F test (prob) [df _r , df _{ur}]	2.21(0.000) [100,91]		1.81(0.027) [97,86]	
H ₀ : No fixed effect or fit in regression				
F test (prob) [df _r , df _{ur}]	2.33(0.044) [5,186]		2.51(0.023) [6,177]	
H ₀ : No fit in the regression				
F test (prob) [df _r , df _{ur}]	2.13(0.000) [95,91]		1.70(0.007) [91,86]	
H ₀ : No fixed effect				
Log likelihood	-250.07		-232.10	
Restricted Log likelihood	-368.38		-334.37	
Chi-sq (prob) [df]	236.62(0.000) [100]		204.55(0.000) [97]	
Variable	Coefficient	t stat	Coefficient	t stat
Change in distance to station (km)	0.269 (0.094)	2.875	-0.078 (0.085)	-0.937
Car number reduction	-0.772 (0.425)	-1.816	0.829 (0.356)	2.327
Car number increase	0.426 (0.439)	0.970	-0.888 (0.453)	-1.963
Change in distance to nearest grocery shop (km)	-0.105 (0.840)	-0.125	-1.568 (0.639)	-2.453
Change in number of grocery shops in a 0.5Km radius	- -	-	-0.101 (0.027)	-3.811
Change in number of non-grocery shops in a 0.5Km radius	- -	-	0.037 (0.022)	1.713
Change in number of grocery shops in a 1Km radius	-0.012 (0.008)	-1.461	- -	-
Classical model statistics test	Log-L	R ²	Log-L	R ²
1.Constant term only	-368.386	0.000	-334.371	0.000
2.Fixed effects only	-262.741	0.667	-254.315	0.581
3.Explanatory variables only	-362.196	0.059	-326.853	0.078
4.Explanatory variables and fixed effects	-250.073	0.708	-232.096	0.671

The coefficient of changes in non-grocery retail on NMM shopping frequency was as expected positive ($p=0.077$), with an average increase in frequency of 3.7% for every one shop increase in a 500m radius.

Although the overall change in eating-out frequency is not statistically significant between time periods, statistically significant changes were observed given activity location and mode. As illustrated in Table 6, models 5, 6 and 7 estimate faraway eating-out frequency by car, faraway eating-out frequency by transit and nearby NMM eating-out frequency respectively. As discussed earlier, the fixed effects were not statistically different from zero hence pooled OLS results are presented. Changes in distance to the closest station are not statistical significant in the car model

or the transit model but have a significant effect on non-motorized eating-out frequency, with an average 38.6% increase for every one kilometer reduction in distance to the station. Changes in car ownership were not significant in any of the models. It is important to note that faraway eating-out frequency by car barely averaged 7.98 times per year, a rather infrequent event. One plausible explanation is that the consumption of alcoholic beverages when eating-out might discourage car travel when participating in such activities, thus reducing the potential of the car as a feasible travel mode alternative, and rendering changes in car ownership insignificant.

Regarding change in number of eating and non-grocery shopping facilities around home location, a positive change in number of facilities is negatively associated with faraway car eating-out frequency, with an estimated semi-elasticity of -0.020, suggesting an average reduction of 2.0% for a one shop increase in a 1 km radius. A similar effect was observed in faraway eating-out frequency by transit, where a one shop increase in a 500 meters radius on average translates into a 2.6% reduction in activity frequency. Conversely, a one shop increase in a 500m radius is associated with a 2.8% increase in nearby non-motorized eating-out frequency; this points to a mode substitution effect between faraway car and transit activities and nearby non-motorized ones.

Table 6. Pooled OLS model estimation results for eating-out frequency

Pooled OLS (robust)	Model 5: Log of yearly car eating-out freq.		Model 6: Log of yearly transit eating-out freq.		Model 7: Log of yearly NMM eating-out freq.	
	Faraway		Faraway		Nearby	
N	190		184		184	
No. of parameters	5		5		5	
Df	185		179		179	
SSR	243.08		276.43		493.80	
Standard error of e	1.15		1.24		1.66	
R.sq.	0.13		0.07		0.16	
F test (prob) [df _r , df _{ur}]	6.76(0.000)	[4,185]	3.26(0.013)	[4,179]	8.75(0.000)	[4,179]
Log likelihood	-293.00		-298.53		-351.90	
Restricted Log likelihood	-305.96		-304.99		-368.32	
Chi-sq (prob) [df]	25.90(0.000)	[4]	12.92 (0.012)	[4]	32.84(0.000)	[4]
Variable	Coefficient	t stat	Coefficient	t stat	Coefficient	t stat
Constant	1.360 (0.222)	6.133	1.148 (0.245)	4.687	1.684 (0.327)	5.144
Change in distance to station	-0.061 (0.086)	-0.709	-0.023 (0.103)	-0.230	-0.386 (0.138)	-2.804
Car number reduction	-0.079 (0.334)	-0.233	0.251 (0.366)	-0.627	-0.465 (0.488)	-0.952
Car number increase	-0.473 (0.361)	-1.310	-0.215 (0.411)	-0.522	0.3632 (0.650)	0.660
Change in number of eating and non-grocery shopping facilities in a 0.5Km radius	- -	-	-0.026 (0.009)	-2.748	0.028 (0.013)	2.250
Change in number of eating and non-grocery shopping facilities in a 1Km radius	-0.020 (0.004)	-4.603	- -	-	- -	-

6. Discussion of findings

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

No significant changes were observed between time periods for leisure activities, suggesting little if any effect from changes in the built environment. Leisure activities might be more related to individual characteristics such as tastes, preferences, lifestyle or social networks characteristics, than to built environment characteristics around home location.

Changes in the built environment however, were found to exert a significant effect on shopping and eating-out frequency given location and travel mode. A mode substitution effect was observed in terms of changes in the number of facilities and activities by location and distance. Positive changes in the number of eating-out and non-grocery shopping facilities were associated with an increase in nearby non-motorized eating-out frequency and a consequent decrease in faraway car and transit frequency. A similar effect was observed in terms of overall nearby activity frequency by NMM and faraway car frequency, although the relationship was not as straightforward, that is, an overall increase in the number of facilities was associated with reduction in activity frequency by car, while an increase in eating-out and non-grocery shopping was associated with non-motorized activity frequency average increase. Mode substitution was also observed in terms of changes in the distance to the station and overall activity frequency by mode. As distance to the nearest station reduces, the frequency of activities reached by NMM increases, while the frequency of activities reached by car decreases. This is largely attributed to a higher concentration of shopping opportunities around transit stations, and diminishing accessibility as distance from the station increases. In terms of shopping frequency, a reduction in the number of vehicles in the household also translated into an increase in nearby NMM shopping frequency and a reduction in faraway car shopping frequency.

Changes in number of vehicles in the household had significant effects on several types of behavior, however, it is important to note that this effect was found to be asymmetric, that is, the effect of a one car increase in the household is not necessarily the same in terms of magnitude (with an opposite direction effect) or statistical significance as the effect of one car reduction, furthermore, this relationship might well be different given the type of activity. Although a one car increase translated in a very significant average increase of activities by car of 207%, a one car reduction was not statistically different from zero. Similarly, although a one car reduction was associated with a mean decrease of faraway car shopping frequency of 77.2%, a one car increase was not statistically significant at any level.

In spite of findings discussed above, there are some limitations to the present study that are worth discussing. Firstly, the effective sample size is rather small, which, particularly in the case of fixed effect models is important, considering the reduction in variability of the data as a result of exclusion of time invariant explanatory variables, resulting in larger standard errors, and lower R-square values. Secondly, regarding external validity of results, it is important to note that given the nature of the study, where only residents of one specific area are considered, inference might only be drawn for a specific socio-economic bracket and for specific changes in the built environment, such as those described earlier. Finally, attitudes and preferences are assumed constant in time. If well this is a reasonable assumption given the short time period elapsed between survey tiers, the alternative hypothesis of a change in attitudes and preferences after

relocation cannot be entirely ruled out. In that sense, a panel survey that also measures attitudes and preferences would be ideal to rule out potential bias.

Nevertheless, despite these limitations, given the aforementioned assumptions, unbiased and consistent effects were estimated regarding the effect of the built environment on activity frequency, and if well the generalization potential is limited, findings presented here do provide some insight on potential effects of retrofitting low density suburban areas by increasing accessibility levels through densification and mixing of land uses, an issue of considerable importance in the Japanese context given the fast depopulation and ageing trend that most suburban areas are experiencing.

7. Conclusion

This study aimed at shedding some light on the existence or not of a causal mechanism between the built environment and travel behavior. Using a panel data from a survey on residents purchasing new apartments on a high density mixed used project adjacent to the Kashiwanoha station, 30 Km away from Tokyo, several models were estimated to test the effect of changes in the built environment on changes in activity frequency by mode. Findings suggest that changes in the built environment in terms of access to potential activity opportunities, exert a significant effect on activity frequency by mode on certain activities such as shopping and eating-out. A mode substitution mechanism from car to non-motorized modes (NMM) was observed given reductions in distance to the nearest train station. A similar mechanism was observed for eating-out frequency given increases in the number of eating-out and non-grocery shopping facilities around home location. Findings also suggest that the effect of changes in number of cars in the household on activity frequency not only is asymmetric, but the nature of this asymmetry is dependent on activity type.

Although some limitations exist, the present study provides empirical evidence on a causal effect of the built environment on certain dimensions of travel behavior. Even though findings might only be generalizable for a certain socio-economic group and certain type of changes in the built environment characteristics, present findings provide a good insight on the potential effects of retrofitting low density suburban areas through densification and mixing of land uses, a critical issue in the Japanese context given rapid aging and depopulation of suburban areas.

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Notes

⁽¹⁾Interested readers are referred to Cao et al.³⁸⁾ for a more detailed review.

⁽²⁾In the USA, neo-traditional neighborhoods are those which are developed in a more compact and mixed manner, resembling the traditional American neighborhoods before the post-war automobile revolution.

⁽³⁾It is assumed that there is a joint decision process where households decide both residential location and number of vehicles to own, as a variable endogenous to travel behavior, fail to control for this might result in estimation bias²¹⁾.

⁽⁴⁾Leisure facilities include sport facilities, game centers, karaoke boxes, parks, museums and theaters.

⁽⁵⁾Note that in the fixed effect model, the cross-sectional values at t_0 and t_1 are introduced in the model, not the first-differenced ones. However, the explanation is given in terms of changes in the variables to help the reader understand the change in the independent variables between time periods.

⁽⁶⁾Semi-elasticity is defined as the percentage change in the dependent variable y given a level change in the explanatory variable x .

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