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

都市の物的環境と交通行動の因果関係に関する研究

−日本の諸都市を事例として−

A dissertation by

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ABSTRACT

The connection between the built environment and travel behavior has been the object of interest of a considerable number of studies in the past twenty years. As concepts such as Smart Growth, Compact Cities and New Urbanism permeate the sustainability discourse, the validity of the argument that high density, compact and mixed-use cities might reduce car use and promote the use of alternative modes hinges on the existence of a true causal mechanism between the built environment and travel behavior.

Of particular importance to the establishment of this causal mechanism is the issue of residential self-selection, where individuals choose their residential location partly to meet their transport preferences. In that sense, failure to control for self-selection might results in biased and inconsistent estimators of the true effect of interest. Although a great number of studies have established significant statistical associations between the built environment and travel behavior, establishing a causal relationship hinges on stronger conditions that are sometimes difficult to meet outside an ideal randomized experiment. This study uses data from several Japanese cities to test the existence of this causal relation using both panel and cross-sectional data.

From a panel data perspective, data from a survey on new-movers to a high-density, mixed-use development in the Kashiwanoha area in Chiba prefecture is used to estimate the effect of changes in the built environment on changes in travel behavior. Findings suggest that a positive change in the number of potential activity opportunities within one's neighborhood results on average in positive changes in the frequency of non-work activities conducted nearby and reached by non-motorized modes. Conversely, it also results in negative changes in the frequency of non-work activities conducted faraway by car. In other words, findings suggest the existence of a causal mode substitution mechanism between nearby activities reached by non-motorized modes and faraway activities reached by car for some non-work activities.

The rest of the dissertation then focuses on the problem of establishing causality using cross-sectional data, which is more widely available in the planning and transport fields. As a first step, significant statistical associations between the built environment and travel behavior are established using data from the 4th Nationwide Person-Trip Survey. Once statistical associations are established, the conditions for establishing causality using cross-sectional data are discussed, and a methodology to estimate causal effects is implemented and validated using data from independent surveys in the cities of Hiroshima and Fukuoka.

The implemented methodology, namely, a propensity score approach with continuous treatments, differs from previous applications in the planning literature in that it relaxes the binary treatment assumption which polarizes the built environment into two extremes (e.g. urban vs suburban), thus allowing for a more precise understanding of the built environment effect on travel behavior at all levels of the urbanization spectrum. The effectiveness of the proposed methodology in reducing bias against OLS was validated via Monte Carlo simulation using several data generating processes. Model results suggest that an increase in urbanization level –as measured by a newly-developed composite index of urbanization– has a negative effect on non-work home-based car trip frequencies, and conversely, a positive effect on non-work home based non-motorized trip frequencies. Similar to panel data findings, results estimates suggest the existence of a causal mode substitution mechanism between car and non-motorized modes given increases in the urbanization level at residential location, thus providing some empirical support to the arguments put forth by compact city advocates.

Keywords: *Travel behavior, Built Environment, Residential Self-selection, Causal Relationship, Urbanization Level, Fixed-Effect Models, Treatment Effect, Propensity Score, Continuous Treatment, Monte Carlo Simulation.*

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CHAPTER 1 INTRODUCTION

1.1 RATIONALE

Against the backdrop of urban sprawl and suburbanization, worsening traffic conditions and declining city centers, recent years have seen a paradigm shift in the conceptualization of what constitutes good urban development. Be it New Urbanism or Smart Growth in the United States, or Compact Cities in the EU and Japan, there seems to be a push from practitioners, academics and some governments towards more transit-connected, compact, and mixed-use cities, and neighborhoods that are more walkable, more bikeable, and more complete (Congress for the new urbanism, 2000; Kaido, 2001; Duany, et al., 2010).

In the particular case of Japan, the former Ministry of Construction (Now Ministry of Land Infrastructure, Transport and Tourism, MLIT) switched its focus from suburban developments to existing urban areas in the late 90's, and some cities like Aomori, Kobe, Kanazawa and Fukui have already incorporated Compact City ideas in their master plans (Kaido, 2001), being the most notable case the one of Toyama, which attracted attention for its successful implementation of the first Light Rail Transit (LRT) system in the country (Takami & Hatoyama, 2008).

It is precisely this push that motivates the present work. More specifically, the implications behind it. One of the main premises behind the Compact City concept is that mixed-use, high density developments can significantly reduce automobile dependency and promote the use of alternative modes such as transit, bicycles or walking, thus resulting in more accessible, livable and inclusive neighborhoods and cities, certainly a non-trivial issue for Japan as it becomes a super-aged society. The underlying assumption behind this premise is that the built environment exerts a strong enough influence on individuals and households to effectively change their travel behavior. In other words, that there exists a non-spurious, causal mechanism behind the built environment-travel behavior connection. The existence or not of this causal relationship between the built environment and travel

behavior is thus a critical point to validate the claims of Compact City advocates, and accordingly, the principal object of interest of this dissertation.

1.2 RESEARCH QUESTIONS

Based on the arguments presented before, the overarching research questions this study seeks to answer are:

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

These research questions are stated in their most general form to allow –as the dissertation develops– for flexibility in the specification of the dimensions of interest in terms of built environment and travel behavior given the type of analysis conducted. In that sense, departing from these overarching questions, each analysis chapter will present its own research questions and hypotheses where more precise definitions of built environment and travel behavior are used.

1.3 OUTLINE OF THE DISSERTATION

This dissertation is organized as follows: Chapter 2 discusses the current state of affairs in the literature regarding the existence of a causal relation between the built environment and travel behavior and discusses the different methodological approaches used to examine this relation. Particular attention is paid to the residential self-selection problem. Chapter 3 presents a panel data empirical analysis of the effect of changes in the built environment on non-work activity frequency using a mixed-use compact development in Kashiwa City as a case study.

In Chapter 4, attention is turned to cross-sectional data analysis, and a preliminary analysis of trip frequency by mode is conducted using data from the 4th Nationwide Person-Trip Survey in order to establish the existence of a significant statistical association between the built environment and travel behavior. Once established, Chapter 5 turns to the problem of estimating a causal relationship with cross-sectional data. Under a treatment evaluation framework a feasible approach to address

the problem is introduced, namely, a propensity score stratification method with continuous treatments. A propensity score empirical application on Hiroshima City is presented in Chapter 6, where urbanization level is used as treatment variable and estimated as a latent construct via confirmatory factor analysis. Having established the strengths and limitations of the proposed approach, Chapter 7 focuses on improving the urbanization level construct in order to address the identified limitations, while Chapter 8 presents another empirical application on Fukuoka City where in addition to using the improved treatment variable, the performance of the propensity score method is measured against ordinary methods using Monte Carlo simulation. In addition, a multi-scale analysis is conducted to analyze how changes in the scale of analysis affect the estimation results.

Finally, Chapter 9 summarizes the main findings of this dissertation and identifies (i) the study limitations and (ii) future research directions on the subject. Figure 1-1 illustrates visually the outline of this dissertation.

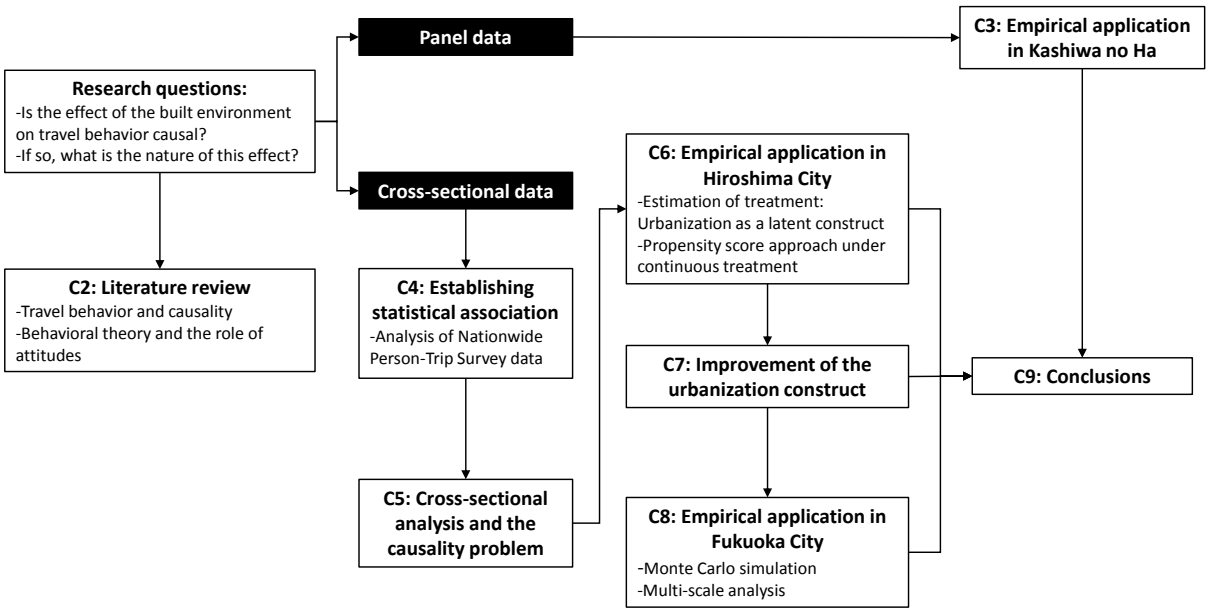


Figure 1-1 Outline of this dissertation

CHAPTER 2 LITERATURE REVIEW

Departing from the necessary conditions to establish the existence of a causal relation, this chapter discusses the current state of affairs of the built-environment travel behavior research. Particular emphasis is put on the residential self-selection problem which has been identified as an important threat to validity. Methodological approaches used to control for residential self-selection are thus discussed both from a cross-sectional and a panel data approach. In addition, as a potentially mediating factor, the role of habits and attitudes in shaping travel behavior is discussed from a behavioral theory perspective.

2.1 BUILT ENVIRONMENT, TRAVEL BEHAVIOR AND CAUSALITY

As concepts such as Smart Growth, Compact Cities and New Urbanism permeate the sustainability discourse, researchers have tried to validate the existence of a causal mechanism that would support the hypotheses put forth by high-density and mixed-use advocates. Although factors such as population density and land use mix have been consistently associated with lower levels of car use (Friedman, et al., 1994; Cervero & Radisch, 1996; Cervero & Kockelman, 1997), and car ownership (Senbil, et al., 2009; Sun, et al., 2012), findings are rather mixed. Meta-analyses conducted by Leck (2006) and Ewing and Cervero (2010) found strong associations between land use mix and travel behavior, 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 behavior, Ewing and Cervero suggested that after controlling for measures of accessibility to destinations, land use mix and street network characteristics, the effect of both population and job densities is relatively weak.

At any rate, although a great number of studies have established significant statistical associations between the built environment and travel behavior, establishing a causal relationship hinges on stronger conditions that are sometimes difficult to meet outside an ideal randomized experiment. Mokhtarian & Cao (2008) 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. Although the first condition might be easily met, establishing effect non-spuriousness and time precedence are non-trivial issues, particularly in the context of cross-sectional analysis.

More generally, largely owing to Campbell (1957; 1969), Meyer (1994) enumerated threats to both internal and external validity for natural experiment studies in economics (see Table 2-1). Although all threats might not necessarily apply, they can be easily extrapolated to urban studies, where true experimental data is largely unavailable if not outright impossible to produce.

Table 2-1 Threats to internal and external validity of economic studies

Threats to internal validity
Omitted variables: variables other than treatment that might explain observed effects
Trends in outcomes: processes that produce changes in observation units given time passage
Misspecified variances: overstatement of test significance due to omission of group errors
Mismeasurement: changes in definitions or survey methods affecting measured variables
Political economy: endogeneity of policy changes due to governmental response associated with outcomes
Simultaneity: endogeneity of explanatory variables due to joint determination with outcomes
Selection: correlation between treatment assignment and outcomes
Attrition: loss of respondents from one time period to the other in non-random manner
Omitted interactions: differential trends in treatment and control groups
Threats to external validity
Interaction of selection and treatment: treatment group not representative of population
Interaction of setting and treatment: treatment effect may vary across geographic or institutional settings
Interaction of history and treatment: treatment effect may differ across time periods

Adapted from Meyer (1994)

One particular threat that has drawn the recent attention of researchers in the planning field is the issue of residential self-selection. Although other validity threats are also important, particular emphasis is made on the self-selection problem as it might be the root cause of other biases, as it will be later discussed. To keep consistency with the rest of the dissertation, the self-selection problem will be illustrated in the framework of program evaluation (Treatment effect evaluation).

Residential self-selection is a type of selection bias; that is, bias stemming from a correlation between treatment assignment and outcomes. In the context of built environment and travel behavior studies, the treatment of interest can be defined as the vector of built environment characteristics whose effect the analyst is interested in measuring (i.e. population density, land use mix, urbanization,

etc.). Given that these characteristics are partly defined by residential location, and that households are free to choose their location, treatment assignment is not random. Residential self-selection bias thus occurs when treatment assignment (residential location) is defined in function of outcomes (the travel behavior of interest). For example, a household or individual that prefers driving might choose to relocate to the suburbs in order to meet this preference.

The next subsections will discuss the different approaches available to address the self-selection issue as well as relevant findings, both from a cross-sectional and a longitudinal approach. Interested readers are also referred to Mokhtarian & Cao (2008) and Cao et al. (2009) for two thorough reviews on the subject. Reviewed studies were classified according to methodology, following a modified version of the classification done by Mokhtarian & Cao: Statistical control, instrumental variables, sample selection and propensity score, discrete choice, and structural equations. A summary of relevant findings of all studies reviewed here is presented in Table 2-2 at the end of this chapter.

2.1.1 Cross-sectional approach

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, and given the necessary conditions discussed earlier, moving beyond statistical association towards establishing causality might be a difficult task. Nevertheless, the approaches discussed here provide some alternatives to at the very least mitigate self-selection bias, and conditional on data availability can be easily applied to longitudinal data.

2.1.1.1 Statistical control

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, the statistical control approach consists on taking the variables that account for self-selection out of the error term and into the explanatory variables, thus eliminating the correlation between the regressors and the error and solving or at least mitigating the endogeneity problem. As a possible mitigation strategy, recent research has pointed to individual

preferences and attitudes on the premise that by accounting for these factors, the factors that drive residential location can be controlled for.

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 methodologies as well as section 2.2 of this chapter for a discussion on attitudes from a behavioral standpoint). 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. Chatman (2009) noted, however, 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 (Cao, et al., 2006; 2009a). Naess (2009) also found significant effects on traveled distances by car, but questioned the extent to which people choose their residential location based on transport considerations.

An alternative approach to addressing the attitudes issue was developed by Schwanen & Mokhtarian (2004) who measured neighborhood type dissonance, that is, the mismatch between an individual's neighborhood preference and his or her current neighborhood type in terms of physical characteristics. Although significant effects stemming from residential mismatch were found, the physical land use structure exerted a stronger influence on distances traveled (Schwanen & Mokhtarian, 2005a) and communting mode choice (Schwanen & Mokhtarian, 2005b)[1], suggesting thus

[1] Given the model structure of this study, it can also be classified in the sample selection category.

a limited self-selection effect. Both studies also suggested that the mismatch issue is more relevant to urban areas where there are more feasible alternatives to the car.

One major limitation in the statsitical control approach is the uncertainty regarding how effective the control variables used to account for residential self-selection are. Although a great number of studies 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), and the extent to which the rather diverse set of existing measures actually capture the self-selection effect remains undefined.

2.1.1.2 Instrumental variables

The second approach to control for self-selection involves purging the built environment variables of its correlation with the error term through instrumental variables. In the context of American or European cities, considering that urban areas developed before the second world war were more compact and mixed, the percentage of buildings built before 1940s and 1960s were used as instruments for the built environment (Boarnet & Sarmiento, 1998; Vance & Hedel, 2007); Findings, however, were different among studies. Although Boarnet and Sarmiento found no significant effects in most models and a high sensitivity to model specification, Vance & Hedel's findings suggest the existence of a casual mechanism between urban form and car use, and robustness to alternative model specifications. Another study by Khattak and Rodriguez (2005) 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.

Although the IV approach remains a feasible alternative to deal with the self-selection-induced endogeneity issue, finding a suitable instrument, that is, an instrument that is correlated with

[2] In the context of the United States, neo-traditional neighborhoods refer to those which are developed in a more compact and mixed manner, resembling the traditional American neighborhoods before the post-war automobile revolution.

the built environment but at the same time exogenous to travel behavior might be a challenging task. Even instruments such as percentage of buildings built before 1940s and 1960s are very location specific and might have limited generalization potential.

2.1.1.3 Sample selection and propensity score

The third approach considers the self-selection problem in a program evaluation framework. In the absence of true experimental data, these approaches aim at overcoming the non-random treatment allocation problem described earlier. To achieve this, two main approaches are highlighted: sample selection models and propensity score models.

The first step for both approaches is to estimate the conditional probability of seeking treatment given a vector of covariates; in the case of a binary treatment, $\Pr(z_i = 1|\mathbf{X_i})$ where z is a binary treatment that takes value 1 when the individual is treated and zero otherwise, and $\mathbf{X_i}$ is a vector of conditioning covariates. For binary treatments, probability is usually estimated via a binary probit or logit model.

In sample selection models (Heckman's sample selection), given an estimated treatment probability, a sample correction coefficient is estimated and introduced in the regression of the outcome variable of interest on all covariates to correct for selectivity bias (Heckman, 1979). Using this approach, Zhou and Kockelman (2008), estimated household vehicle-miles-Traveled (VMT) given a binary treatment of urban vs. suburban residential location and found that 90% of the difference in VMT was attributed to the treatment itself and that self-selection accounted only for 10% of the observed traveled distances. A similar study by Cao (2006) estimated that self-selection accounted for 19% of the observed VMT.

Similar to the sample selection models, propensity score models depart from the estimation of treatment probability. Propensity score matching consists in matching treated and untreated samples given similar treatment probability scores, difference in outcomes between matched pairs are then averaged and the average treatment effect (ATE) estimated (Rosenbaum & Rubin, 1983).

Alternatively, as Rosenbaum and Rubin show, the sample can be stratified given estimated treatment probability and outcomes of subgroups compared, reducing bias up to 95%. Using propensity score matching with different binary treatments (i.e. urban vs. suburban, urban vs. exurban etc.), Cao et al. (2010) found a positive association between vehicle miles drive and distance from the city center, with the impact of self-selection ranging from 0.05% to 52%, depending on the treatments considered.

Concerning walking behavior, Boer et al. (2007) estimated treatment effects for several built environment features and found that higher levels of business diversity and four way intersections were on average associated with more walking. Through propensity score stratification, Cao (2010) found that residents living in neo-traditional neighborhoods tend to walk more than their suburban counterpart; furthermore, he found that failure to account for self-selection might result in overestimating the effect of the built environment on walking frequency by 64% and 17% for utilitarian trips and recreational trips respectively.

Although the studies discussed so far do evidence the potential of propensity score methods to reduce selection bias, in most studies reviewed the built environment is polarized to a binary treatment (usually urban vs. suburban), in itself a rather strong assumption that ignores the spectrum of variability in terms of how “urban” or how “suburban” a neighborhood might be. In other words, a binary treatment considers all neighborhoods within each treatment class identical in its built environment features, thus making the estimates insensitive to variations in neighborhood compositions.

As an aside, it is important to note that as extensions to the binary treatment approach. Multi-valued treatment approaches have been proposed by Lee (1983), in the form of a multinomial logit-OLS two stage model, and by Imbens (2000) and Imai & van Dyk (2004) which can also be applied to ordinal multi-level treatments and continuous treatments respectively. While these approaches are certainly promising improvements, to the author’s best knowledge they have yet to be operationalized into the transportation field.

2.1.1.4 Discrete choice: Joint residential location – travel behavior models

The discrete choice approach consist on jointly modelling the residential location process and the travel behavior variable of interest. The simplest definition of the urban residential location choice mechanism comes from bid-rent economic theory, where the residential location choice results from a tradeoff between transportation costs and land prices, defined as a function of distance from the city center (Alonso, 1964; Lowry, 1964; Harris, 1966; Mills, 1967). These monocentric models, although appealing for its analytical power and simplicity have been criticized for its incapability to reflect a more realistic pattern of spatial development (Waddell, 1993).

An alternative approach to the monocentric models came with the advent of discrete choice theory. Households are assumed to make residential location choice by considering the characteristic of a set of alternatives and selecting the utility maximizing alternative. Following work by Lerman (1976) and Mcfadden (1978), the multinomial logit model (MNL), as well as its successive generalizations have become the workhorses of residential location analysis. Discrete choice theory has also allowed for the joint modelling of residential location with mid-term and short-term decisions such as car-ownership and travel mode, thus accounting for its interdependent nature. These multi-dimensional choice models can be estimated either as a joint multinomial model when the alternatives share only observed attributes, or as nested models when alternatives share also unobserved attributes and the Independence of Irrelevant Alternatives (IIA) assumption fails to hold (Ben-Akiva & Lerman, 1985).

Salon (2006) estimated a joint multinomial logit of residential location, car ownership and walking levels and suggested that the share of the total elasticity that is not due to residential self-selection was between 50% and 75% for most areas of New York City. Cervero (2007) estimated a nested logit of residential location (a binary choice of living close to a rail station or not) and rail commuting. His findings suggest that around 40% of the observed higher share of rail commuting in areas close to transit was due to self-selection effects.

Expanding on work by Bhat and Guo (2007), Pinjari et al. (2007) developed a joint discrete choice model of residential location and commuting mode that accounted for unobserved factors affecting individual sensitivity to location and mode choice in the error specification. Results pointed to the existence of both observed and unobserved factors affecting residential self-selection, but noted the existence of significant effects by built environment factors such as density, accessibility and land use mix levels on commuting mode choice. Pinjari et al. (2011) further extended this approach by modelling interdependencies to account not only for residential location and mode choice but also car and bicycle ownership using a mixed joint logit model. Their findings also suggested the existence of significant self-selection effects, yet even after controlling for these effects, built environment characteristics both at residential and workplace location had significant effects on commuting mode choice.

2.1.1.5 Structural equations models

Although relatively recent in its applications to transport and planning, structural equation models have been largely used in psychology and social sciences. As noted by Golob (2003), important advantages of SEM models against other linear-in-parameter statistical models include (i) the treatment of exogenous and endogenous variables as random variables with error measurement (ii) the possibility of estimating latent variables with multiple indicators, (iii) overall models are tested rather than individual coefficients, (iv) the modeling of mediating effects and (v) the possibility testing of coefficients across multiple groups in a sample.

A study by Bagley & Mokhtarian (2002) on distance traveled using SEM found a very small effect of residential location characteristics on travel behavior once attitudes and lifestyle preferences are controlled for, which in turn had the strongest effects on travel demand. Scheiner and Holz-Rau (2007) suggested, however, that socio-demographic characteristics (defined in the study as life situation) had a stronger effect on VKT than lifestyle, whose effect was limited once the former were controlled for. By affecting residential location decision choices that in turn affect VKT, lifestyle was

found to have an indirect effect. Although urban form variables were found to be significant, in terms of effect magnitude as compared to residential location attitudes, findings were mixed and varying given changes in model specification.

The effect of built environment has also been found to differ given activity types, having very little effect on work and leisure travel distances, but the strongest influence on maintenance task distances (Scheiner, 2010). Scheiner also found that lifestyle plays an important role explaining leisure distances and interestingly enough, did not find any considerable effect on travel distances by residential location preferences.

2.1.2 Quasi-longitudinal approach

Quasi-longitudinal studies consist on gathering information of past behavior retrospectively in the absence of true panel data, thus including a time component in the model. Using the same dataset, Handy et al. (2005) found from a cross-sectional approach no significant association between VKT and built environment features after controlling for attitudes. On the other hand, from a quasi-longitudinal perspective, changes in accessibility perception were significantly associated with changes in driving levels. In terms of non-motorized travel behavior, Handy et al. (2006) found significant changes in walking levels given changes in accessibility perception, but suggested that attitudes (which were measured at only one point in time) play a larger role in explaining changes in bicycle use levels.

Quasi-longitudinal SEM studies of changes in travel mode use levels have also suggested significant effects of changes in built environment characteristics as a result of residential relocation on changes in mode use. Suburban relocation was associated with higher driving levels and less transit and non-motorized travel, an effect opposite to the one observed after urban relocation (Scheiner & Holz-Rau, 2013), supporting evidence was provided by Cao et al. (2007) who also found reduced driving levels and increased walking given relocation to neo-traditional neighborhoods.

Although quasi-longitudinal data helps bridge some of the limitations of cross-sectional data, it is not without limitations. Of particular concern is the reliability or quality of retrospective data, as respondents might forget past behavior, or their responses might be influenced by most recent behaviors. Furthermore, unfeasibility of retrospective measurement does not allow for measuring changes in attitudes and preferences over time. If unmeasured, the effect of these changes is likely to confound with the measured built environment effects (Cao, et al., 2007).

2.1.3 Longitudinal approach

Among all approaches 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 the ideal randomized experimental situation. Natural experiments examine outcomes in observations in treatment and control groups that are not randomly assigned, but where there is an exogenous source of variation in the variables that determine treatment assignment (Meyer, 1994).

A fixed effect model on walking by Wells and Yang (2008) found that moving to places with fewer cul-de-sacs was associated with an average increase in walking. Incidentally, the study also found an unexpected decrease in walking levels given an increase in the number of service jobs per resident. It is important to note, however, that the study was conducted with a very small sample size of 32 and targeted a very specific socio-demographic cohort, 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 that the built environment had no significant effect (Eid, et al., 2008), 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.

From a more planning-oriented perspective, Krizek (2003) 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.

Although ideal, natural experiments involve considerable increases 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.

2.2 BEHAVIORAL THEORY AND THE ROLE OF ATTITUDES AND HABITS

As it was discussed in section 2.1, recent research has pointed to the role of attitudes (and to a lesser extent of habits) on understanding the factors mediating between household residential location and travel behavior. This section will thus review the role of attitudes and habits in explaining travel behavior from a behavioral theory standpoint.

Ajzen's Theory of Planned Behavior (TPB) departs from the premise that behavior is a function of salient beliefs relevant to the behavior, and thus are the main determinants of a person's intentions and actions (Ajzen, 1991). The TPB identifies three salient beliefs; (i) behavioral beliefs, (ii) normative beliefs, and (iii) control beliefs, which are assumed to affect attitudes toward the given behavior, subjective norms and perceived behavioral control respectively. Attitudes refer to the individual's own appraisal –either negative or positive– about the behavior; subjective norms refer to social pressure a person perceives as being subjected to in terms of performing the behavior in question or not; and perceived behavioral control refer to the individual`s own perception on whether he or she can successfully perform the given behavior or not. It is precisely in the inclusion of control beliefs where the theory of planned behavior differs from its predecessor, the theory of reasoned action (TRA). By doing so, the TPB it is able to deal with behaviors over which individuals do not have complete

volitional control (Ajzen, 1991). Figure 2-1 illustrates the conceptual structure of the Theory of Planned Behavior.

In a meta-analysis of 185 independent studies, Armitage and Conner (2001) found that on average, the TPB explains 39% of the variance in intentions to perform a behavior and 27% of variance of actual behavior. This difference in predictive power of intention and actual behavior suggests a dissonance between stated intentions and performed behaviors, which is known as intention-behavior inconsistence. This inconsistency might arise from forming unrealistic intentions as a result of a misjudged perceptions of behavioral control, a change of mind due to weak intentions or even as a result of forgetting one's intentions (Garling, et al., 1998). Garling et al. suggested that while these might give rise to "false alarms" when intentions are stated yet not performed, other inconsistencies might result in "intention misses" when an individual performs a behavior without having stated any intentions to do so. These misses are attributed to either impulsive behaviors or habitual ones, behaviors towards which intentions might have little predictive power over.

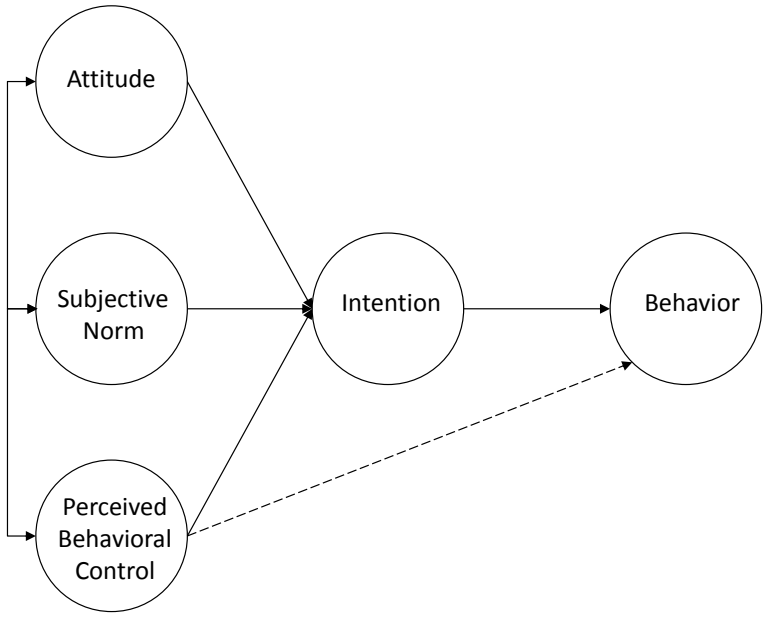


Figure 2-1 Conceptual Structure of the Theory of Planned Behavior. (Adapted from Ajzen, (1991))

One of the main criticisms against the TPB is that it does not consider the effect of habits on behavior. Triandis (1977) suggested that behavior was determined by a tradeoff between intentions and habits. This tradeoff, formalized in Triandis' Theory of Interpersonal Behavior, can expressed as:

$$(1) \qquad P_a = (w_h \cdot H + w_i \cdot I) \cdot F$$

where P_a is the probability of an act, H and I are measures of habit and intentions weighted by w_h and w_i respectively, and F is a measure of conditions facilitating the performance of the act. Triandis suggested that while new behavior is dominated by intentions, as behavior frequency increases, the magnitude of w_h gets larger while that of w_i reduces making habit the dominant factor.

A meta-analysis of behavioral studies by Oulette & Wood (1998) provided some support to the argument put forth by Triandis (1970) based on empirical evidence. Oulette & Wood found that under stable decision contexts, past behaviors were better predictors of behavior executed on daily or weekly basis than intentions, which had far more explanatory power on behaviors that tend not to become habitual. These findings reinforce the argument that intentions and past behaviors function as alternative predictors of behavior, according to whether or not activities might turn into habits through repeated execution.

Explaining the cognitive process behind this tradeoff, Verplanken et al. (1997) suggested –as illustrated in figure 1.2– that as habits become stronger the information searching process about possible alternatives diminishes and individuals become less attentive to external information. As a result, goal activation directly conducts to the habitual choice.

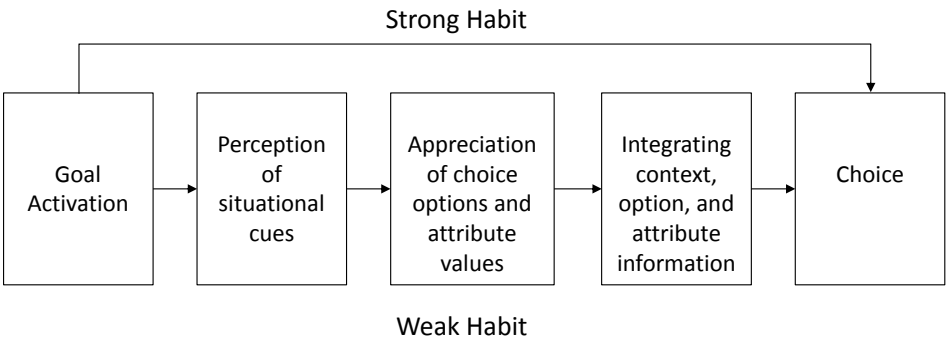


Figure 2-2 Process model of making choices by individuals with weak and strong habit (Adapted from Verplanken et al. (1997))

Ajzen (1991), however, argued that the significance of the habit construct, usually treated as a function of past behavior might be the result of significant factors unaccounted for in a given model; consequently the construct would seem to capture the effect of past behavior on later behavior. Ajzen further argued that in order to consider habit as an explanatory variable to the TPB, it must be defined independently of past behavior. In response, Verplanken et al. (1994) developed a measure of habit that does not rely on measurements of past behavior, called the Response Frequency Method (RF). Instead of reporting past behavior, respondents were asked to select what travel mode they would choose for a series of imaginary trips, (i.e. "go to the beach with friends").

Empirically, Verplanken et al. (1994) found that the correlation between car choice attitude and car choice behavior consistently decreased as habit strength increased. Supporting evidence was provided by Verplanken et al. (1997), who tested mode choice information seeking behavior for hypothetical travel scenarios among individuals according to their habit strength in a laboratory setting. Results suggested that those who had formed strong habits inspected less information on different alternatives prior to making their decision than their weak habit counterpart. Fujii et al. (2001) suggested that this kind of information seeking process might lead to an inaccurate perception of the attributes of alternative choices, and consequently serve to reinforce the given habit.

Overcoming some of the limitations associated with laboratory experiments, mainly, the issue of external validity, Verplanken et al. (1998) tested the effect of habits on behavior prediction using

travel behavior revealed preference data from a seven day travel diary and found that the interaction habit and intention significantly increased the explanatory power of the regression over that of the TPB determinants. Furthermore, a simple regression slope analysis of intention on behavior according to habit strength levels –as illustrated in Figure 2-3– showed that the slopes for the intention parameter flattened as habit strength increased, supporting the hypothesis that the predictive power of intentions decreased as habit strength increased.

On the other hand, Bamberg et al. (2003b) argued that if well past behavior and habits seem to be stronger predictors of later behavior, past behavior is also a function of salient beliefs. In that sense, stability of behavior is not necessarily a result of a strong habit but a result of stability of intentions given an unchanged decision making context. It is thus hypothesized that even for frequently executed behaviors there is some level of awareness in the decision making process. Accordingly, were the decision making context to change, the intention and behavior cognitive basis of the individual will also be likely to change in light of the new information received (Bamberg, et al., 2003b).

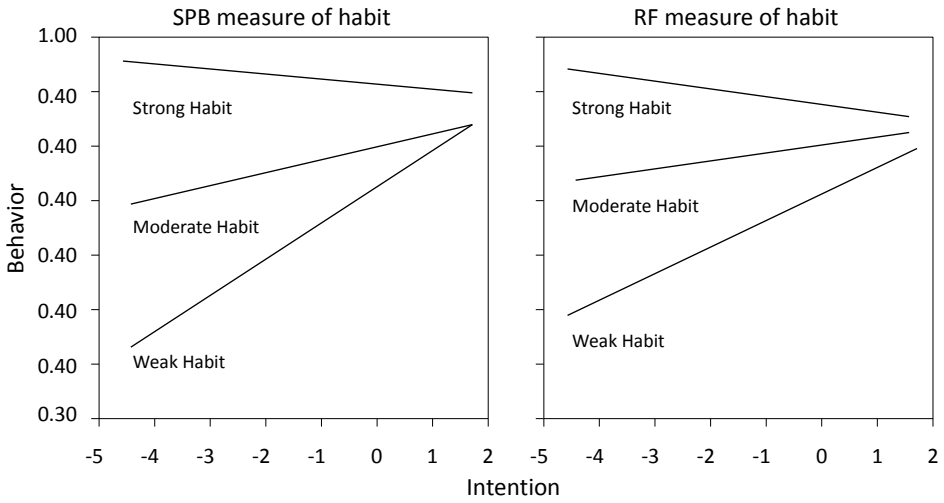


Figure 2-3 Standardized regression slopes of intention on behavior for weak, moderate, and strong habit individuals (Adapted from Verplanken et al. (1998))

Bamberg et al. (2003a) analyzed through a longitudinal study the effects of an intervention on university students' bus use. The intervention consisted on the introduction of a one year pre-paid

bus ticket to campus. Data was gathered on present and past travel behavior to campus as well as on the determinants identified by the TPB in two tiers; two months before the intervention was implemented and 8 months after. The program achieved a doubling of the bus modal share among the sample, who mostly were riding the bus as a substitute for car use. Results of structural equation models also showed that if well the effect of past behavior had a strong effect on later behavior on the first tier of the study, it lost its predictive ability following the intervention. In that sense, the behavioral shift was attributed to a change in students' attitudes, subjective norms and perception of behavioral control regarding riding the bus to campus, thus strengthening the intentions to conduct the desired behavior (Bamberg, et al., 2003a). Bamberg et al. also point out that past behavior might be a good predictor of later behavior only to the extent the decision making context is stable.

Bamberg et al. (2003b) conducted an experimental study where a free public transport ticket valid for all transport facilities in the city of Stuttgart, Germany, was given to a random sample of new-movers six months after moving into the city. As in the previous study, the experimental group was asked to answer a questionnaire both before moving, and after the intervention. An increase in public transport use was observed in the experimental group; furthermore, structural equations model results showed that the TPB explained 66% of the variance in actual travel behavior. In addition, it was found that although habit had a negative effect on attitude, perception of behavioral control and subjective norms, it had no direct effect on future behavior, providing empirical evidence to the hypothesis that the effect of past behavior or habit on later behavior rather than a causal relation, might well be a statistical association.

Another experimental study was conducted by Fujii & Kitamura (2003) where one month free bus ticket were provided to university students in Kyoto, Japan. The experimental group consisted of those students that are drivers and received the bus ticket versus a control group consisting of drivers who did not received any ticket. Data was gathered on the TPB salient beliefs and the response frequency method was used to measure habit. Results showed a 20% increase in bus ridership after

the intervention on the experimental group against the control group, an increase attributed to the "correction" of the negative attitude towards bus use that drivers might have through actual experience. Fujii and Kitamura, however, pointed out that habit might be a stronger determinant of travel behavior than attitudes and highlighted the importance of unfreezing habits to achieve behavioral change.

Interestingly enough, in spite of the theoretical differences between the different theories discussed above, in their practical implications both theories might converge at the same point. On the one hand supporters of the TPB suggest that since even habitual behaviors are a function of salient beliefs, a change in the decision making context will be accompanied by a re-assessment of choice alternatives (Ajzen, 1991; Bamberg, et al., 2003a; Bamberg, et al., 2003b). On the other hand, supporters of the habit theory recognize that attempts to change attitudes might be successful in achieving a behavior change if the habit in question is broken, and the individual is forced to establish new behavioral patterns as a result of a "habit unfreezing event", such as policies that might reduce the attractiveness of the behavior in question (Verplanken, et al., 1994; Verplanken, et al., 1998; Fujii & Kitamura, 2003).

Table 2-2 Summary of travel behavior studies addressing the self-selection issue

Approach	Study	Analysis method	Travel behavior variables(TB)	Built environment variables (BE)	Attitudes (AT)		Findings and conclusions
					Variables	Analysis and input	
Group I SC	Kitamura et al. (1997)	OLS regression	Trip frequency by mode Share of trips by mode (Car, PT, NMM)	Neighborhood characteristics Neighborhood perception Distance to transit Distance to facilities Density (Z) Land use mix (Z) Transit access(Z)	Travel attitudes Personality and lifestyle factors.	Factor analysis	Socio-demographics and BE are associated with travel. Attitudinal variables explained a higher proportion of the variation in the data. Attitudes might be more strongly associated with travel behavior than land use.
Group I SC	Chatman (2005)	Negative binomial regression	Non-work trip frequency by mode (Car, PT, NMM)	Retail employment (1/4mi) Retail employment (1 mi) Distance to downtown 4-way intersections (1/4mi) Region indicator	Transport access preference	Direct input	Residential self-selection might lead to misestimating the effect of BE on trip frequency. Measured bias reduces the magnitude of the effect but does not render it statistically insignificant. Self-selection might also bias the BE effect towards zero.
Group I SC	Schwanen and Mokhtarian (2005)	Multinomial Logit	Commute mode	Region indicator (Alternative specific)	Travel attitudes Personality and lifestyle factors Residential preference match	Factor analysis	There are significant differences in commute mode choice given neighborhood type match/mismatch. Well matched urbanites have the highest probability of commuting by transit or non-motorized modes. In suburban areas, BE seems to exert a stronger influence on behavior than preferences. In urban areas, the effect of both factors is more balanced, mainly due to a larger choice availability.
Group I SC	Cao et al. (2006)	Negative binomial regression	Strolling freq. Walk to store frequency	Neighborhood characteristic perception Shop features and perception	Residential preference	Direct input	Pedestrian shopping trips are more likely to be explained by self-selection. Neighborhood perception explained better strolling frequency
Group I SC	Naess (2009)	[1]OLS regression [2]Binary Logit	[1]Travelled distance by car [2]Car ownership (having at least one car)	Distance to CBD Distance to second order urban center(ln) Distance to closest rail station(ln) Inhabitants + workplaces per hectare	Attitude towards car driving[1] Residential preference[2]	[1] Direct input [2]Segmentation according to preference	BE exerts a significant effect on car distances even after accounting for self-selection. The extent to which people choose their residential location based on transport considerations might be limited.
Group I SC	De Vos et al. (2012)	Descriptive analysis	Travel mode choice (Car, PT, NMM)	Considered indirectly	Residential preference match	Factor analysis	Transit and non-motorized modes used is mainly determined by attitudes; Car use on the other hand is more influenced more by BE than preferences.

Approach	Study	Analysis method	Travel behavior variables(TB)	Built environment variables (BE)	Attitudes (AT)		Findings and conclusions
					Variables	Analysis and input	
Group I SC	Frank et al. (2007)	[1]Logistic regression [2]OLS regression	[1] Likelihood to conduct: Walk trips Non-discretionary walk trips Discretionary walk trips [2]VMT	Walkability index	Residential preference	PCA	Neighborhood preferences and BE affect choice to walk and driven distances. Those matching their walkable neighborhoods preferences walked more for both discretionary and non-discretionary trips; individuals preferring non-walkable environments walked less regardless of neighborhood walkability. Regardless of preferences and socio-demographics, individuals in more walkable neighborhoods drove less.
Group I SC	Cao et al. (2009)	Seemingly unrelated regression Random effect model	Non-work trip frequency by mode (Car, PT, NMM)	Neighborhood type dummy Number of business types within 400m Number of business types within 800m Distance to closest: Library, theater, post office Neighborhood perception	Residential preference Travel attitudes	Factor Analysis	After accounting for individual attitudes and preferences, neighborhood characteristics were associated with travel behavior, particularly non-motorized trip frequency. Land use mix might support car trip substitution with non-motorized modes.
Group II IV	Boarnet and Sarmiento (1998)	2SLS Regression	Car trip frequency	BE (L)(Z): Pop. density, retail and service employment density, % of street grids within 1/4mi (L)[only] *Instruments (L)(Z):* % blacks, % Hispanics, % buildings before 1940s, % buildings before 1960s	Not included	N/A	Land use variables were statistically insignificant in most model specifications. Model specification and variable measurement can affect estimation results considerably.
Group II IV	Khattak and Rodriguez (2005)	[1]Binary logit [2]Negative binomial regression [3]OLS regression	[2]Trip frequency (Car, external, walking) [3]Trip distance (Work, non-work) [3]Trip duration	[1]BE(L): Neighborhood type (Conventional, neo-traditional) *Instruments:* Non-transport related attitudes and residential preferences	Non-transport related attitudes Non-transport related residential preferences	Direct input	After controlling for self-selection, households in neo-traditional neighborhoods make similar number of trips, yet fewer car trips, external trips and travel shorter distances. Evidence of car trip substitution was observed.

Approach	Study	Analysis method	Travel behavior variables(TB)	Built environment variables (BE)	Attitudes (AT)		Findings and conclusions
					Variables	Analysis and input	
Group II IV	Vance and Hedel (2007)	[1]Binary probit [2]OLS regression	[1]Car use [2]Travelled distance by car	Commercial density (Z) Street density(Z) Commercial diversity(Z) Walking time to transit(Z) *Instruments (Z):* % buildings before 1945 % buildings 1945-1985 %residents over 65 yrs % of foreign residents	Not considered	N/A	Urban form is a significant determinant of car travel. IV for commercial density, street density were negatively associated with traveled distances, while minimum distance to transit was positively associated with car distances.
Group III **SS**|PS	Schwanen and Mokhtarian (2005)	[1]Binary probit [2]Tobit regression	[1]Travel mode choice [2]Weekly distance traveled by mode	Region indicator	Travel attitudes Personality and lifestyle factors Residential preference match	Factor analysis	There are significant differences in weekly traveled distances given neighborhood type match/mismatch. Matched urbanites exhibit the overall and private car distances are shortest. Probability of using rail and non-motorized modes is highest.
Group III SS|**PS**	Boer et al. (2007)	Propensity score stratification: Binary logit	Probability of making at least one walking trip in a day	No. of different business(L) Housing density (L) Parking pressure(L) Block length(L) Fraction of 4-way crossings(L)	Not considered	N/A	Higher levels of business diversity and four way intersections were associated with more walking. The effects of density on walking were mixed.
Group III **SS**|PS	Zhou and Kockelman (2008)	Heckit model: [1]Binary probit [2]OLS regression	[2]Household VMT	[1]BE(L): Neighborhood type (Urban, suburban) *Selection model regressors:* Socio-demographics only	Not considered	N/A	Treated households (living in suburban neighborhood) exhibit 20.2 more VMT than their untreated counterpart. 90% of the difference in VMT attributed to BE 10% of the difference attributed to self-selection.
Group III **SS**|PS	Cao (2009)	Heckit model: [1]Binary probit [2]OLS regression	[2]Vehicle miles driven(ln)	[1]BE(L): Neighborhood type (Urban, suburban) *Selection model regressors:* Residential preference and travel attitudes Socio-demographics	Residential preference Travel attitudes	Factor analysis	The ATE of neighborhood type was 25.8 miles/week, or 16% of overall individual driving. ATT (treatment is living in suburban neighborhood) was 33.8 miles/week. The effect of self-selection (ATT-ATE) was estimated at 8 miles/week.

Approach	Study	Analysis method	Travel behavior variables(TB)	Built environment variables (BE)	Attitudes (AT)		Findings and conclusions
					Variables	Analysis and input	
Group III SS|**PS**	Cao (2010)	Propensity score stratification: [1]Binary logit	Walking trip frequency (Recreational Utilitarian)	[1]BE(L): Neighborhood type (Urban, suburban) *Propensity score regressors:* Residential preference and travel attitudes Socio-demographics	Residential preference Travel attitudes	Factor analysis	When not controlling for self-selection, the effect of BE on travel behavior is likely to be overestimated. Propensity score method might reduce selection bias up to 90%, but not fully mitigate it.
Group III SS|**PS**	Cao et al. (2010)	Propensity score matching: [1]Binary logit	Vehicle miles driven	[1]BE(L): Neighborhood type (Urban, suburban, inner-ring suburban, exurban) *Propensity score regressors:* Residential preference Socio-demographics	Residential preference	Direct input	VMD was positively associated with distance from the city center. The impact of residential location ranged from 3.0 to 12.6 miles per day. The impact of self-selection ranged from 0.176 to 3.7 miles per day.
Group IV **JDC**|NL	Salon (2006)	Joint Multinomial logit	Walking levels (Walks between 1% and 50% of trips; walks 50% or more of trips)	BE(L): Population density Distance from Midtown Manhattan Retail density Subway line availability	Not Included	N/A	The share of the total elasticity that is not due to residential self-selection ranged between 50% and 75% for most areas.
Group IV **JDC**|NL	Pinjari et al. (2007)	Joint Multinomial logit	[1]Residential location* [2]Commute mode choice	Number of households(ln)(Z) Density (Z): Household, jobs Residential area ratio (Z) Single family housing ratio(Z) Land use mix (Z) Recreation accessibility(Z) Street block density(Z) Bicycle facility density(Z) Availability of PT to work(Z) Transit access time to stop(Z)	Not Included	N/A	Significant observed factors contribute to residential self-selection. After controlling for self-selection BE attributes such as accessibility, density, and land use mix have a significant effect on commuting mode choice.

Approach	Study	Analysis method	Travel behavior variables(TB)	Built environment variables (BE)	Attitudes (AT)		Findings and conclusions
					Variables	Analysis and input	
Group IV **JDC**|NL	Pinjari et al. (2011)	Joint Multinomial logit (Mixed Multi-Dimensional Choice Model)	[1]Residential location* [2]Car ownership* [3]Bike ownership* [4]Commute mode choice	Number of households(ln)(Z) Density (Z): Household, jobs Commercial area ratio (Z) Land use mix (Z) Number of physically active recreation centers(Z) Number of natural recreation centers(Z) Street block density(Z) Bicycle facility density(Z)	Not Included	N/A	Several inter-dependencies were identified: Significant self-selection effects were identified. Significant endogeneity effects of Car ownership and bicycle ownership on commute mode choice. Significant presence of common unobserved factors affecting choice decisions. Significant unobserved heterogeneity. Failing to account for these interdependencies might results in biased estimators.
Group IV JDC|**NL**	Cervero (2006)	Nested logit	(Upper)Choice to live near transit* (Lower) Choice to commute by rail	Workplace within 1/4, 1/2, 1 mile from station. Job accessibility index Travel time ratio Population density (L)	Not included	N/A	An estimated 40% of the higher rail commuting shares among workers is attributed to self-selection.
Group IV **MDCEV**	Pinjari et al. (2009)	Multiple discrete continuous extreme value (MNL-MDCEV)	Residential location* Activity time use	Number of households(ln)(Z) Density (Z): Household, jobs Commercial area ratio (Z) Land use mix (Z) Number of schools (Z) Number of physically active recreation centers(Z) Number of natural recreation centers(Z) Street block density(Z) Bicycle facility density(Z) Commute time	Not included	N/A	Significant observed and unobserved individual factors explain residential self-selection. Households make residential location and activity time use decisions jointly consistent with lifestyle preferences and attitudes. After controlling for self-selection, BE variables are still significant; however, the effect of BE on activity time use is rather small. Socio-demographics have a much larger impact on activity time use.
Group V SEM	Bagley and Mokhtarian (2002)	Structural equations model	VMT(ln) Transit miles traveled(ln) NM miles traveled(ln)	Residential location: (Traditional, suburban) Commuting distance	Travel attitudes Personality and lifestyle factors.	Factor analysis	In terms of direct and total effects lifestyles and attitudinal variables had the greatest effect on travel demand. When controlling for attitudes and lifestyle preferences, residential location had little impact in travel behavior.
Group V SEM	Scheiner and Holz-Rau (2007)	Structural equations model	Share of trips by mode (Car, PT, NMM) VKT	Urbanization composite scale (Pop. density + Land use mix) (L) Density of supply of activities: Retail, services, leisure (L) Quality of PT supply (L)(Z)	Residential preference Lifestyle factors	Factor analysis	Life situation exerts a stronger effect on travel mode than lifestyle. The effect of lifestyle on travel behavior is rather indirect, by influencing location attitudes and location choice that in turn affect travel behavior.

Approach	Study	Analysis method	Travel behavior variables(TB)	Built environment variables (BE)	Attitudes (AT)		Findings and conclusions
					Variables	Analysis and input	
Group V SEM	Scheiner (2010)	Structural equations model	Trip distances: (Work, leisure, maintenance)	Job supply quality Number of shopping opportunities in a 650 radius Number of leisure opportunities in a 650 radius	Residential preference Lifestyle factors	Direct input	Lifestyle had a significantly strong effect on leisure trip distances. Minor effects for other trip purposes. All trip purposes influenced considerably by social status. BE has very little effect on job and leisure distances, yet was the most important factor influencing maintenance tasks. Residential location preference did not have any considerable impact on traveled distances.
Group VI Quasi-Longitudinal (SC)	Handy et al. (2005)	[1]OLS Regression [2]Ordered probit	[1]VMD (ln) (Cross-section) [2] Δ Driving levels (Quasi-longitudinal)	[1]Neighborhood perception [2]Δ Neighborhood perception [2]Number of groceries in 1600m [2]Number of pharmacies in 1600m [2]Number of theaters in 400m	Travel attitudes	Factor Analysis	Cross-sectional analysis: No significant associations with BE features once attitudes were accounted for. Quasi-longitudinal analysis: Changes in accessibility (perception) were the most important factor explaining changes in driving levels. Increased accessibility (perception) was negatively associated with either a small increase or a large decrease in driving.
Group VI Quasi-Longitudinal (SC)	Handy et al. (2006)	Ordered probit	Δ Walking levels Δ Biking levels	Distance to closest: Bank, health facility Number of: Banks in 800m, types of business in 1600m household maintenance facilities in 1600m Δ Neighborhood perception	Residential preference Travel attitudes	Factor analysis	Regarding changes in walking levels, the impact of changes in accessibility (perception) are significant; however, only large improvements in accessibility will produce substantial changes. Attitudes play a larger role in explaining changes in biking than BE.
Group VI Quasi-Longitudinal (SEM)	Cao et al. (2007)	Structural equations model	Δ Driving levels Δ Walking levels Δ Auto ownership*	Neighborhood characteristics Neighborhood perceptions Δ Neighborhood perception Distance to nearest fast food Number of leisure business within 1600m	Residential preference Travel attitudes	Factor analysis	A significant direct impact of self-selection on travel behavior was found. Neighborhood preferences have a direct effect on residential location that in turns affects travel behavior. Changes in BE had a significant effect on changes in travel behavior, even after accounting for current attitudes. BE effects were estimated to be as large as that of socio-demographics.
Group VI Quasi-Longitudinal (SEM)	Scheiner and Holz-Rau (2013)	Structural equations model	Δ Driving levels Δ PT use levels Δ Walking levels Δ Biking levels Δ Auto ownership*	Δ Urbanization levels Δ Quality of shopping facilities and services Δ Quality of PT service Δ Satisfaction level with PT	Not included	N/A	Changes in BE resulting from residential relocation induce significant changes in mode use. Changes in BE are among the most important factors affecting mode use change. The extent to which self-selection affects travel behavior could not be clearly assessed.

Approach	Study	Analysis method	Travel behavior variables(TB)	Built environment variables (BE)	Attitudes (AT)		Findings and conclusions
					Variables	Analysis and input	
Group VII Panel Data	Krizek (2003)	OLS regression	Δ VMD Δ PMT Δ Number of tours Δ Number of trips/tour	Commute distance, Δ Commute distance NA, ΔNA RA, ΔRA Workplace NA, ΔWork RA Workplace NA, ΔWork RA	Not included	N/A	Households moving to a traditional neighborhood (higher neighborhood accessibility) on average reduce their total Vehicle miles driven and person miles traveled.
Group VII Panel Data	Wells and Yang (2008)	Fixed effect model	Number of steps per week (Post moving)	ΔNumber of service jobs per resident ΔNumber of cul-de-sacs	Not included	N/A	Moving to places with fewer cul-de-sacs was associated with an average increase of walking. Increase in number of service jobs per resident was associated with less walking. *Small sample size (N=32)
Group VII Panel Data	Grafova et al. (2013)	Difference in difference model	Not included. Dep. variable: Δ Self-assessed health**	Neighborhood economic environment	Not included	N/A	Cross sectional estimates of the effect of neighborhood economic environment are underestimated.
Group VII Panel Data	Eid et al (2008)	First difference regression	Not included. Dep. variable: Δ Body Mass Index**	Δ Residential sprawl index Δ Land use mix: number of retail shops and churches in the neighborhood	Not included	N/A	No significant relation was found between changes in BMI and residential sprawl or land use mix. Higher obesity rates were attributed entirely to self-selection of obesity prone individuals into sprawling, low land use mix neighborhood.

*Modeled simultaneously with travel behavior variables.

**Not directly related to travel behavior, but addressing the residential self-selection issue, hence of methodological interest.

SC: Statistical control; **IV:** Instrumental variable; **SS:** Sample selection; **PS:** Propensity score; **JDC:** Joint discrete choice; **NL:** Nested logit; **VMT:** Vehicle miles traveled; **VMD:** Vehicle miles driven; **VKT;** Vehicle kilometers traveled; **PMT:** Person miles traveled; **BE:** Built Environment; **PT:** Public transport; **NMM:** Non-motorized modes; **LU:** Land use; **(L):** Local/Neighborhood Scale;**(Z):** Aggregated large Zonal Scale [TAZ, ZIP code area]; **(ln)** natural log; **NA:** Neighborhood accessibility; **RA:** Regional accessibility

CHAPTER 3 PANEL DATA ANALYSIS: EMPIRICAL APPLICATION ON THE KASHIWA NO HA CAMPUS DISTRICT

3.1 INTRODUCTION

This chapter addresses the causality problem discussed in the previous chapter via panel data analysis. Data from a survey on new-movers to a high density mixed-use development in the Kashiwanoha area in Chiba prefecture was used to estimate fixed effect models to test the effect of changes in the built environment on changes in 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.

3.2 HYPOTHESES STATEMENTS

In order to overcome some of the limitations of cross-sectional studies discussed in Chapter 2, this section addresses the built environment and travel behavior relationship from a panel data perspective. Specifically, the main objective is to understand how changes in the land use characteristics around home location affect changes in activity frequency by mode. This motivates the following hypotheses:

- 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.

- 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, it is hypothesized that there exists a mode substitution mechanism between private vehicle and non-motorized modes given an increase in accessibility to any given activity around home location.

3.3 STUDY CHARACTERISTICS

To test the hypotheses stated in Section 3.2, 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 in Chiba prefecture, at roughly 30 Kilometers from Tokyo. The area is connected to Tokyo via the Tsukuba Express railway line (see Figure 3-1).

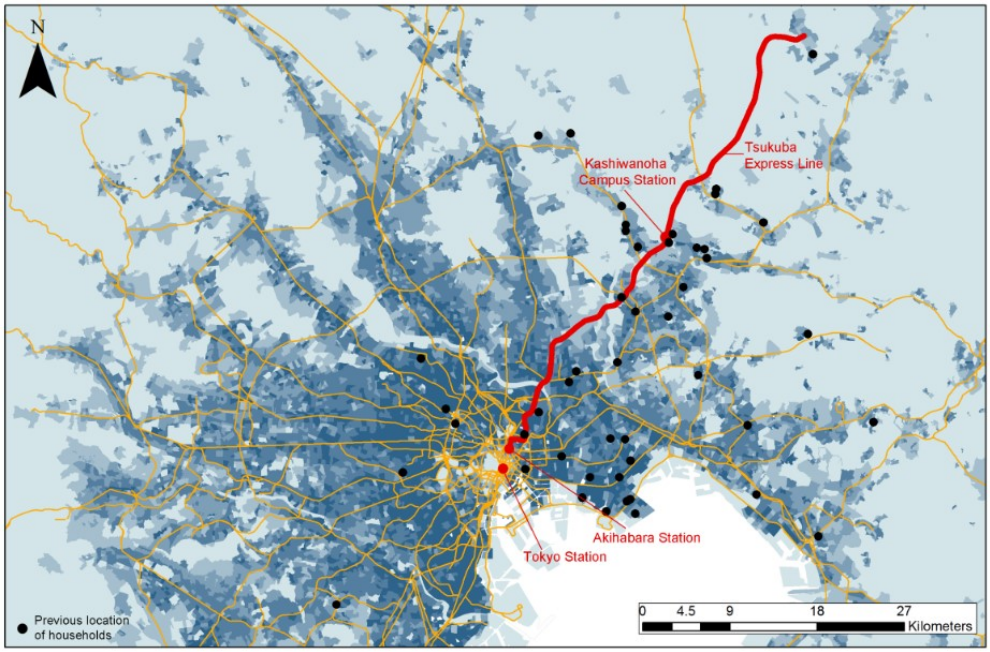


Figure 3-1 Location of the Park City Kashiwanoha Campus and previous location of households

As of 2012, the Kashiwanoha area exhibited a population of 3,277 inhabitants with a population density of 1,731 persons per km^2, roughly half of the density Kashiwa city, and approximately one eight of the density of the 23 special wards of the Tokyo Metropolitan Area (MIC, 2005; Kashiwa City, 2012).

Against this suburban background, the Park City Kashiwanoha Campus Project –which constitutes the target area of this analysis– 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 industry (Kashiwa City, 2011). 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 (see Takahashi et al. (2008) for a mobility management study using Tier 1 and Tier 2). Given the existence of systematic inconsistencies between behavioral intention and actual behavior

(Fujii & Garling, 2003), 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 3-1.

Table 3-1 General socio-demographic 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	-	0.00	1.00	98
Driver’s license	0.49	-	0.00	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	0.00	4.00	49
Number of cars in household	0.92	0.34	0.00	2.00	49
Number of bicycles in household	1.55	1.17	0.00	6.00	49

Regarding pre-moving residential location of households (see Figure 3-1), 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%).

3.4 MODEL SPECIFICATION AND CAUSALITY CONDITIONS

Given the described study characteristics, the analysis can be thought of in terms of a natural experiment where residential relocation to the Kashiwanoha Campus Project can be though as the treatment of interest, and the changes in built environment characteristics as the treatment variables of interest. However, as discussed earlier, 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 the causal effect estimates are biased and inconsistent due to self-selection bias.

To address the self-selection problem, a fixed effect model is specified. 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

$$(2) \qquad Y_{i1} = \alpha_i + \boldsymbol{\beta}\mathbf{X_{i1}} + \boldsymbol{\gamma}\mathbf{Z_{i1}} + \varepsilon_{i1}$$

$$(3) \qquad Y_{i0} = \alpha_i + \boldsymbol{\beta}\mathbf{X_{i0}} + \boldsymbol{\gamma}\mathbf{Z_{i0}} + \varepsilon_{i0}$$

where Y_i is the outcome variable of interest. α is the unobserved individual heterogeneity, or individual fixed effect. $\mathbf{X_i}$ is a vector of time changing individual and household characteristics. $\mathbf{Z_i}$ is a vector of time changing built environment characteristics, and ε is the idiosyncratic error term.

The key identifying condition for this model is the strict exogeneity assumption where, following the notation of Wooldridge (2010), the conditional expectation of the idiosyncratic error term is 0

$$(4) \qquad E(\varepsilon_{it}|\mathbf{X_{it}}, \mathbf{Z_{it}}, \alpha_i) = 0$$

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. In that sense, a key assumption is that the factors that account for residential self-selection and car ownership, 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).

Another key implication of Equation (4) is that conditional on $\boldsymbol{X_{it}}$ and $\boldsymbol{Z_{it}}$ there will be no difference in the means between treated and untreated groups. This is a non-trivial assumption, given that the available data only allows for a one group pretest-posttest analysis. That is, changes in the treatment group (movers) without a comparable untreated group (non-movers). However, as

discussed in Chapter 2, travel behavior is rather stable in either unchanged decision contexts or in the presence of strong habits, which provides some empirical support for this assumption. Furthermore, as equations (2) and (3) show, in addition to changes in the built environment as a result of residential relocation, other time-changing household and individual socio-demographic characteristics are also controlled for, thus accounting for potential changes in individuals' decision making contexts or "habit unfreezing" events.

Now, in order to properly estimate the coefficients of interest, it is necessary to weed out the fixed effect α. By taking the deviation from mean at each time t, we then get a time-demeaned equation for the i_{th} individual

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

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, under the assumptions previously stated $\boldsymbol{\gamma}$ retrieves the causal effects of changes in the built environment on changes in activity frequency by mode.

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 analysis. Furthermore, fixed effect models have also been shown to be more robust to attrition bias than random effect models (Verbeek & Nijman, 1992), an issue present in most practical applications of panel data studies.

3.5 VARIABLE DESCRIPTION

3.5.1 Dependent variables

To gather information on activity frequency, 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. Only activities that start from home are considered in this analysis.

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 3-2). 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 location (Scheiner, 2010). Another important factor might be the rather disparate aggregation of leisure activities under the

leisure category. In that sense, it is possible 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 3-2 Paired sample t-test of changes in activity frequency (result highlights)

Variable Name	Mean at t_0	Mean of difference	% mean change	S.D. of difference	S.E. of mean	t-stat
Total activity frequency	371.48	31.43	8%	176.28	18.09	1.74
Total activity frequency | Nearby	**250.11**	**51.52**	**21%**	**157.86**	**16.11**	**3.20**
Total activity frequency | Faraway	**121.37**	**-23.84**	**-20%**	**93.23**	**9.47**	**-2.52**
Total shopping frequency	**161.23**	**32.92**	**20%**	**102.14**	**10.32**	**3.19**
Total education frequency	**15.09**	**-6.74**	**-45%**	**30.63**	**3.09**	**-2.18**
Total eating-out frequency	44.82	-0.87	-1%	60.16	6.10	-0.14
Total leisure frequency	80.05	2.20	3%	111.27	11.30	0.19
Changes in activity frequency given travel mode						
Total activities by car	**73.30**	**-30.02**	**-41%**	**87.89**	**9.26**	**-3.24**
Total activities by transit	45.93	-2.90	-6%	96.99	10.22	-1.94
Total activities by NMM	**143.42**	**56.50**	**39%**	**171.14**	**18.04**	**3.13**
Total leisure by car | Faraway	10.03	-4.26	-42%	25.96	2.63	-1.61
Total leisure by transit | Faraway	9.40	4.21	45%	34.92	3.55	1.19
Total leisure by NMM | Nearby	50.20	-0.01	0%	94.14	9.66	0.00
Total shopping by car | Faraway	**15.80**	**-6.87**	**-43%**	**29.83**	**3.01**	**-2.28**
Total shopping by transit | Faraway	**9.85**	**0.93**	**9%**	**33.75**	**3.40**	**2.72**
Total shopping by NMM | Nearby	**57.32**	**47.02**	**82%**	**93.61**	**9.66**	**4.87**
Total education by car | Faraway	2.63	-0.30	-11%	10.20	1.03	-0.29
Total education by transit | Faraway	4.27	1.77	41%	30.61	3.09	0.57
Total education by NMM | Nearby	10.54	-4.54	-43%	28.32	2.88	1.57
Total eating-out by car | Faraway	**7.98**	**-6.44**	**-81%**	**17.96**	**1.82**	**-3.53**
Total eating-out by transit | Faraway	**8.63**	**-6.65**	**-77%**	**21.34**	**2.16**	**-3.06**
Total eating-out by NMM | Nearby	**16.27**	**16.41**	**101%**	**47.16**	**4.86**	**3.37**

*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% increase of nearby non-motorized shopping. Conversely, average faraway shopping frequency by car 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 analysis is to explore changes in travel behavior.

3.5.2 Independent variables

As described in the Section 3.4, explanatory variables consist of time-variant individual and household variables and built environment variables. Among socio-demographics, time-changing variables include household size, number of workers, commuting frequency, as well as number of cars and bicycles in the household. Changes in number of cars in the household range from -1 to +1, with 12.2% of the households reducing one unit, and an equal percentage 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[3] 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 facilities 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 tell us the whole story 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. This suggests a rather spread-out distribution of the change. Table 3-3 summarizes the explanatory variables as well as the average changes and standard deviations of changes after moving to Kashiwa[4].

[3] Leisure facilities include sport facilities, game centers, karaoke boxes, parks, museums and theaters.

[4]) 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.

Table 3-3 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
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.

3.6 ESTIMATION RESULTS

Given the hypotheses stated in Section 3.2, seven models are estimated using log-transformed variables as follows (Note that all the models refer to activities that start from home):

- Model 1: Log of yearly activity frequency by car
- Model 2: Log of yearly activity frequency by NMM
- Model 3: Log of yearly shopping frequency by car |Faraway

- Model 4: Log of yearly shopping frequency by NMM | Nearby
- Model 5: Log of yearly eating-out frequency by car | Faraway
- Model 6: Log of yearly eating-out frequency by transit | Faraway
- Model 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 this null hypothesis suggests that the explanatory variables fail to explain the observed outcomes. 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 (H_0: No fixed effect in regression); a failure to reject this 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 these cases, the pooled OLS results are presented instead.

Table 3-4 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 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.

Table 3-4 . 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) [df_r, df_{ur}] H_0: No fixed effect or fit in regression	3.26(0.000)	[91,84]	2.42(0.000)	[91,84]
F test (prob) [df_r, df_{ur}] H_0: No fit in the regression	7.05(0.000)	[4,171]	5.54(0.000)	[4,171]
F test (prob) [df_r, df_{ur}] H_0: No fixed effect	2.79(0.000)	[87,84]	2.133(0.000)	[87,84]
Log likelihood	-249.72		-242.44	
Restricted Log likelihood	-382.68		-359.50	
Chi-sq (prob) [df]	265.91(0.000)	[91]	226.69(0.000)	[91]
Variable	**β**	**t-Stat**	**β**	**t-Stat**
Change in distance to station (Km)	**0.246 (0.066)**	**3.723**	**-0.402 (0.137)**	**-2.919**
Car number reduction	-0.086 (0.273)	-0.313	0.327 (0.474)	0.690
Car number increase	**2.075 (0.488)**	**4.250**	-0.255 (0.390)	-0.654
Change in number of eating and non-grocery shopping facilities in a 0.5Km radius	- -	-	**0.022 (0.010)**	**2.090**
Change in overall number of facilities in a 1Km radius	**-0.010 (0.003)**	**-3.084**	- -	-
	Log-L	**R^2**	**Log-L**	**R^2**
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

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

symmetric, 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 is 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 is 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 3-5, models 3 and 4 focus on faraway shopping frequency by car and nearby shopping frequency by NMM respectively. Changes in distance to the nearest train station are not statistically different from zero in the NMM model. On the other hand, the effect on faraway car shopping is 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 is 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 is 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 is not statistically different from zero. Interestingly enough, this relation is opposite to the one observed in model 1,

where a one-car increase is 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 3-5 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}] H_0: No fixed effect or fit in regression	2.21(0.000)	[100,91]	1.81(0.027)	[97,86]
F test (prob) [df_r, df_{ur}] H_0: No fit in the regression	2.33(0.044)	[5,186]	2.51(0.023)	[6,177]
F test (prob) [df_r, df_{ur}] H_0: No fixed effect	2.13(0.000)	[95,91]	1.70(0.007)	[91,86]
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	**β**	**t-Stat**	**β**	**t-Stat**
Change in distance to station (km)	**0.269** **(0.094)**	**2.875**	-0.078 (0.085)	-0.937
Car number reduction	**-0.772** **(0.425)**	**-1.816**	**0.829** **(0.356)**	**2.327**
Car number increase	0.426 (0.439)	0.970	**-0.888** **(0.453)**	**-1.963**
Change in distance to nearest grocery shop (km)	-0.105 (0.840)	-0.125	**-1.568** **(0.639)**	**-2.453**
Change in number of grocery shops in a 0.5Km radius	- -	-	**-0.101** **(0.027)**	**-3.811**
Change in number of non-grocery shops in a 0.5Km radius	- -	-	**0.037** **(0.022)**	**1.713**
Change in number of grocery shops in a 1Km radius	-0.012 (0.008)	-1.461	- -	-
	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

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 3-2 and Table 3-3. 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.

The coefficient of changes in non-grocery retail on NMM shopping frequency is 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 are observed given activity location and mode. As illustrated in Table 3-6, 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 are not significant in any of the models.

Table 3-6 Pooled OLS model estimation results for eating-out frequency

Pooled OLS (robust)	Model 5: Log of yearly car eating-out freq. Faraway		Model 6: Log of yearly transit eating-out freq. Faraway		Model 7: Log of yearly NMM eating-out freq. 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	**β**	**t-Stat**	**β**	**t-Stat**	**Variable**	**β**
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**	- -	-	- -	-

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. Another possible explanation is that faraway eating-out activities are conducted after work, thus making them dependent on commuting mode.

Regarding changes 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.

3.7 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.

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 a reduction in activity frequency by car, while an increase in eating-out and non-grocery shopping was associated on average with an increase in non-motorized activity frequency. Mode substitution was also observed in terms of changes in distance to 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 analysis that are worth discussing. First, the effective sample size is rather small, an especially important issue in the case of fixed effect models when considering the issue of reduced variability discussed earlier. Second, 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. 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 and given the aforementioned assumptions, unbiased and consistent effects were estimated regarding the causal effect of the built environment on activity frequency. 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.

CHAPTER 4 ESTABLISHING STATISTICAL ASSOCIATION USING CROSS-SECTIONAL DATA

4.1 INTRODUCTION

Having addressed the causality problem through a panel data approach, subsequent chapters focus on the causality issue from a cross-sectional perspective. In order to motivate the problem, this chapter first seeks to establish a significant statistical association between the built environment and travel behavior. To do so, data from the 4th Nationwide Person-Trip Survey is used to model non-work trip frequencies by mode, incorporating a set of residential location preference variables in addition to the usual built environment variables. To account for unobserved heterogeneity of the sampled cities, random parameter count models are estimated. As expected, and consistent with findings from the literature, significant statistical associations were found between the built environment and individual preferences with non-work trip frequency by mode. Furthermore the effects of population density, car ownership and some access preference traits were found to be heterogeneous for some modes.

4.2 HYPOTHESES STATEMENTS

Following the findings presented in Chapter 2, a set of preference variables are used to control for the direct effect of attitudes on travel behavior. In that sense, the following hypotheses are put forth.

- After controlling for modal access preference at the time of relocation, gross population density, and density of commercial facilities are negatively associated with home-based non-work car trip frequencies and positively associated with home-based transit and non-motorized trip frequencies.

- After controlling for modal access preference at the time of relocation, Closeness to a transit station is negatively associated with home-based non-work car trip frequencies and positively associated with home-based transit and non-motorized trip frequencies.

4.3 STUDY CHARACTERISTICS AND VARIABLE DESCRIPTION

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 4-1) 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 7,408 individuals across 57 cities.

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

Group	Type	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

4.3.1 Dependent variables

Three dependent variables were used in this analysis to describe individual travel behavior: Number of home-based non-work trips[5] 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 was 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.

4.3.2 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

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

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.

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 4-2 summarizes respondents’ modal access preferences when choosing their current residential location. Given that categories are non-mutually exclusive, joint preferences are also presented. Finally, Table 4-3 summarizes the descriptive statistics of the variables relevant to this study.

Table 4-2 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 4-3 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	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

4.4 MODEL STRUCTURE

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 4-1.

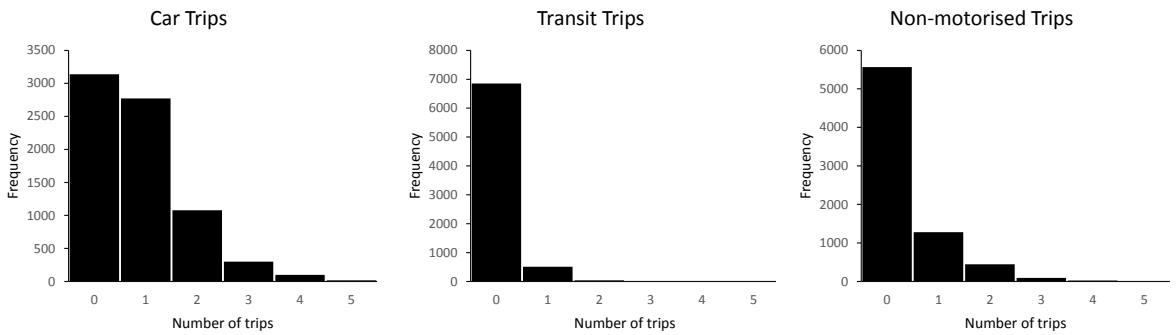


Figure 4-1 Histogram of non-work trips by mode

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

$$(6) \qquad Y|\boldsymbol{v}_{i,c} = e^{\beta'_{i,c}\boldsymbol{X}_{i,c}}$$

and in the negative binomial case

$$(7) \qquad Y|\boldsymbol{v}_{i,c} = e^{\beta'_{i,c}\boldsymbol{X}_{i,c}+\varepsilon_i}$$

given

$$(8) \qquad \beta_{i,c} = \beta + \boldsymbol{\Gamma}\boldsymbol{v}_{ic}$$

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 *i*th 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). [6]

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

$$(9) \qquad \hat{E}\left(\beta_{i,c}\middle|Y_i,\boldsymbol{X_i}\right) = \frac{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{\beta}_{i,c,r}\hat{L}\left(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,\beta,r}}\right)}{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{L}\left(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,\beta,r}}\right)}$$

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 rth simulated unconditional estimate $\hat{\beta}_{i,c,r}$. For each random parameter, the standard deviation of the distribution is estimated as

$$(10) \qquad \widehat{S.D.}\left(\beta_{i,c}\middle|Y_i,\boldsymbol{X_i}\right) = \sqrt{\hat{E}\left(\beta_{i,c}^2\middle|Y_i,\boldsymbol{X_i}\right) - \left(\hat{E}\left(\beta_{i,c}\middle|Y_i,\boldsymbol{X_i}\right)\right)^2}$$

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

$$(11) \qquad \hat{E}\left(\beta_{i,c}^2\middle|Y_i,\boldsymbol{X_i}\right) = \frac{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{\beta}^2{}_{i,c,r}\hat{L}\left(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,t,\beta,r}}\right)}{\left(\frac{1}{R}\right)\sum_{r=1}^{R}\hat{L}\left(Y_i,\boldsymbol{X_i},\boldsymbol{v_{i,t,\beta,r}}\right)}$$

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:

$$(12) \qquad R^2_{DEV\ Poisson} = 1 - \frac{\sum_{i=1}^{N}\left\{Y_i\, log\left(\left(\frac{\hat{\mu}_i}{\bar{Y}}\right) - (\hat{\mu}_i - \bar{Y})\right)\right\}}{\sum_{i=1}^{N}\left\{Y_i\, log\left(\frac{Y_i}{\bar{Y}}\right)\right\}}$$

and

[6] 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.

$$(13) \qquad R^2_{DEV\ NegBin2} = 1 - \frac{\sum_{i=1}^{N}\left\{Y_i\, log\left(\frac{Y_i}{\hat{\mu}_i}\right) - (Y_i + \hat{\alpha}^{-1})\, log\left(\frac{Y_i + \hat{\alpha}^{-1}}{\hat{\mu}_i + \hat{\alpha}^{-1}}\right)\right\}}{\sum_{i=1}^{N}\left\{Y_i\, log\left(\frac{Y_i}{\bar{Y}}\right) - (Y_i + \hat{\alpha}^{-1})\, log\left(\frac{Y_i + \hat{\alpha}^{-1}}{\bar{Y} + \hat{\alpha}^{-1}}\right)\right\}}$$

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 are 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).

4.5 ESTIMATION RESULTS

Random parameter Poisson models are estimated for the car trip and transit trip frequency models, while in the non-motorized case random parameter negative binomial models are estimated. Models are 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 behavior was 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 are used to assess the difference in parameters across cities. In that sense, Departing from the initial specification, random parameters that are not statistically significant and

whose confidence intervals exhibited little variation among groups are fixed across groups and the models are then re-estimated[7].

Estimation results evidence the existence of unobserved heterogeneity in the built environment and preference effects in all models. Final estimation results are summarized in Table 4-4, Table 4-5, and Table 4-6. Figure 4-2 illustrates the 95% confidence intervals of the estimated random parameters for each city.

Table 4-4 Random parameter Poisson regression estimates of non-work trips by car

	B.E. Model		**Full Model**	
N	7408		7408	
Number of groups	57		57	
Log-likelihood (Constant)	-9038.57		-9038.57	
Log-likelihood (Random)	-8471.35		-8453.98	
σ^2 = LL(β)-LL(C)	0.063		0.065	
Base model Deviance R^2 (S.D. Model)	0.028		0.028	
Deviance R^2	0.038		0.039	
Parameters	***β***	**t-Stat**	***β***	**t-Stat**
Constant	**-0.216**	**-7.595**	**-0.219**	**-7.595**
Individual and household attributes				
Age	**0.004**	**3.686**	**0.003**	**3.016**
Male	**-0.184**	**-4.232**	**-0.182**	**-4.183**
Worker	**-0.252**	**-7.909**	**-0.258**	**-7.999**
Number of cars in household	**0.025**	**5.673**	**0.023**	**5.135**
Driver's license	**0.950**	**20.085**	**0.923**	**18.131**
Number of bicycles in household	-	-	-	-
Nuclear household	**0.226**	**7.253**	**0.212**	**6.097**
Single household	**-0.263**	**-3.863**	**-0.269**	**-3.765**
Couple household (Under 65 years)	**0.126**	**3.221**	**0.103**	**2.611**
Built environment characteristics				
Log of population density	**-0.018**	**-6.581**	**-0.017**	**-5.875**
Log of commerce density	-	-	-	-
Train station within 800m	**-0.081**	**-2.615**	**-0.074**	**-2.305**
Residential access preference				
Car access preference	-	-	**0.051**	**3.078**
Transit access preference	-	-	-	-
Non-motorized access preference	-	-	**-0.080**	**-2.627**

Random parameters are highlighted in black

All else equal and regardless of travel mode, men carry on average less non-work trips than women. Similarly, worker status is associated with less non-work trips irrespective of mode; this difference is considerably larger for non-motorized trips. In terms of household structure composition,

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

belonging to a nuclear household is positively associated with car trip frequency and negatively associated with transit frequency, while living alone is associated with less car travel and more non-motorized trips. Positive and significant associations are also observed between young couple households and both car and non-motorized trips.

Table 4-5 Random parameter Poisson regression estimates of non-work trips by transit

	B.E. Model		Full Model	
N	7408		7408	
Number of groups	57		57	
Log-likelihood (Constant)	-2145.03		-2145.03	
Log-likelihood (Random)	-1887.74		-1874.22	
σ^2 = LL(β)-LL(C)	0.120		0.126	
Base model Deviance R^2 (S.D. Model)	0.104		0.104	
Deviance R^2	0.169		0.208	
Parameters	***β***	**t-Stat**	***β***	**t-Stat**
Constant	**-0.975**	**-9.858**	**-0.929**	**-9.199**
Individual and household attributes				
Age	-	-	-	-
Male	**-0.437**	**-4.533**	**-0.417**	**-4.213**
Worker	**-0.288**	**-3.102**	**-0.292**	**-3.003**
Number of cars in household	**-0.155**	**-5.959**	**-0.136**	**-5.225**
Driver's license	**-0.254**	**-2.115**	**-0.251**	**-2.052**
Number of bicycles in household	-	-	-	-
Nuclear household	**-0.469**	**-3.802**	**-0.471**	**-3.772**
Single household	-	-	-	-
Couple household (Under 65 years)	-	-	-	-
Built environment characteristics				
Log of population density	**0.040**	**4.486**	**0.023**	**2.644**
Log of commerce density	-	-	-	-
Train station within 800m	**0.202**	**2.489**	**0.152**	**1.866**
Residential access preference				
Car access preference	-	-	**-0.248**	**-2.513**
Transit access preference	-	-	**0.174**	**3.573**
Non-motorized access preference	-	-	-	-

Random parameters are highlighted in black

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 meters from a transit station is 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, living near a transit station is associated with 15% more transit trips.

In terms of random parameters, estimated values reported in the output tables 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 4-2 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.

Table 4-6 Random parameter negative binomial regression estimates of non-work trips by NMM

	B.E. Model		**Full Model**	
N	7408		7408	
Number of groups	57		57	
Log-likelihood (Constant)	-5855.111		-5855.111	
Log-likelihood (Random)	-5162.1		-5098.17	
σ^2 = LL(β)-LL(C)	0.118		0.129	
Base model Deviance R^2 (S.D. Model)	0.148		0.148	
Deviance R^2	0.197		0.220	
Parameters	***β***	**t-Stat**	***β***	**t-Stat**
Constant	**-0.406**	**-9.358**	**-0.435**	**-9.497**
Individual and household attributes				
Age	**0.004**	**3.696**	**0.003**	**2.666**
Male	**-0.362**	**-7.081**	**-0.335**	**-6.062**
Worker	**-0.840**	**-16.357**	**-0.823**	**-15.886**
Number of cars in household	**-0.093**	**-8.217**	**-0.078**	**-6.674**
Driver's license	-	-	-	-
Number of bicycles in household	**0.176**	**10.165**	**0.164**	**9.124**
Nuclear household	-	-	-	-
Single household	**0.151**	**1.936**	**0.168**	**2.134**
Couple household (Under 65 years)	**0.107**	**1.878**	**0.110**	**1.912**
Built environment characteristics				
Log of population density	-	-	-	-
Log of commerce density	**0.105**	**8.820**	**0.075**	**5.482**
Train station within 800m	**0.137**	**3.005**	**0.101**	**2.245**
Residential access preference				
Car access preference	-	-	**-0.084**	**-3.918**
Transit access preference	-	-	**0.109**	**2.196**
Non-motorized access preference	-	-	**0.415**	**5.926**
Dispersion parameter				
α	**2.860**	**8.682**	**3.350**	**7.148**

Random parameters are highlighted in black

As Figure 4-2 illustrates, population density is negatively associated with car trip frequencies and positively associated with transit trip frequencies. The effect of population density on car trip frequency is highly heterogeneous with considerable variations among cities. Not so the case of transit trip frequency where all confidence intervals hover around the same ranges.

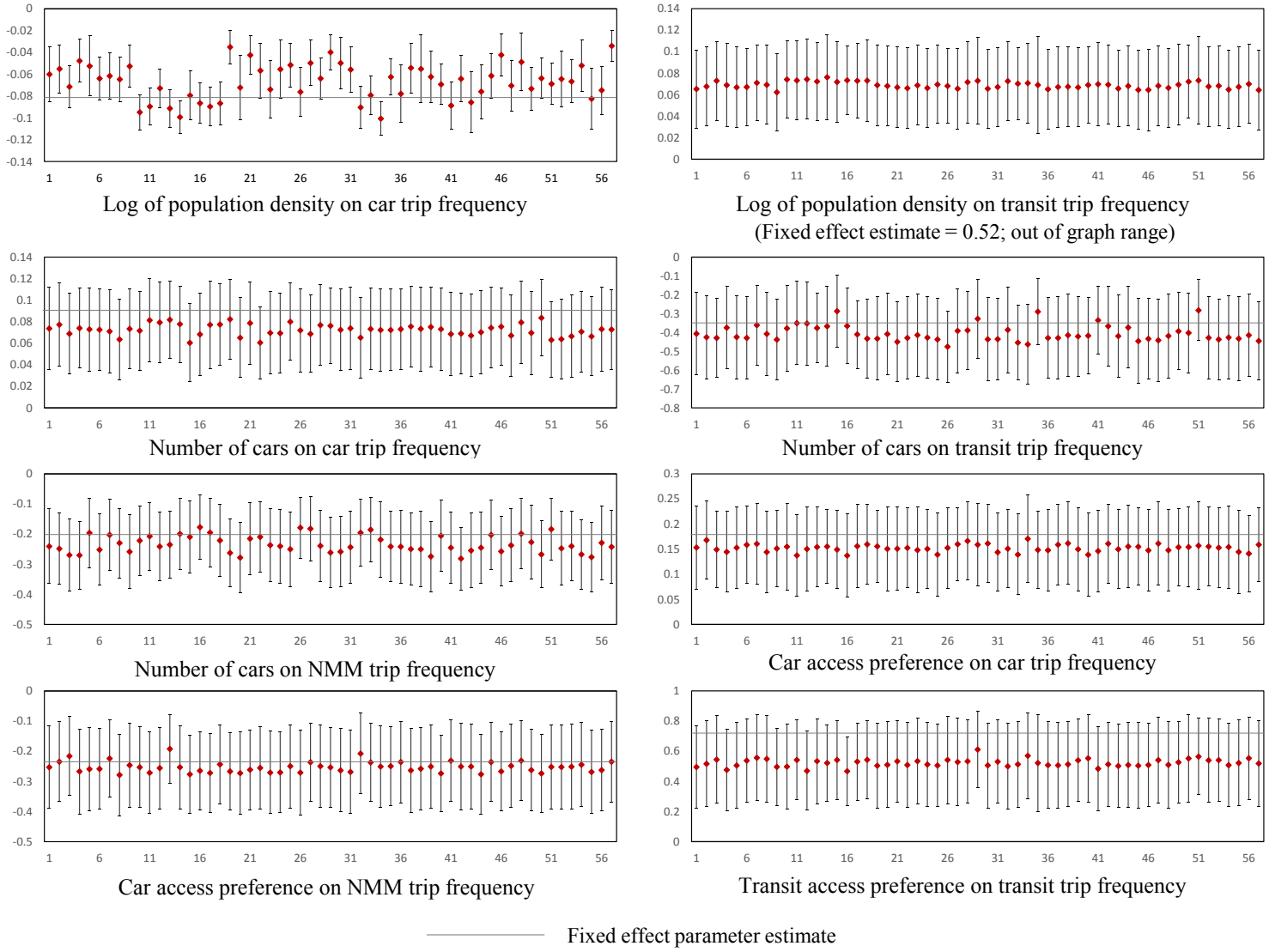


Figure 4-2 Confidence intervals of estimated random parameters for full models

In a similar manner, the effect of number of cars is 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 is positively associated with car trip frequency and negatively associated with other modes, being the effect is heterogeneous for both car and non-motorized modes. Transit access preference is 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 is rather small.

Regarding the overall explanatory power of the models, as Table 4-7 illustrates, compared to the fixed parameter models, random parameter models result in better fit models as measured by the likelihood ratio tests. For car trip frequency, although deviance R^2 was low, socio-demographics explains the larger share of the variation in the data, while for transit trips, the combined explanatory power of built environment and preference variables is roughly the same to socio-demographics. In terms of non-motorized trips, socio-demographics explains the largest share of the variation, but the inclusion of built environment and preferences variables result in considerable improvements in explanatory power.

Although direct comparison with other studies is difficult due to differences in modelling approaches and reported statistics, an informal comparison is 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 4-7 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

4.6 DISCUSSION OF FINDINGS

Estimated results suggest significant statistical associations between the built environment and home-based 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). This effect was found to be heterogeneous for car and transit trips. 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. More importantly, the effect of some preference traits were found to be heterogeneous across different cities.

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.

Although a statistically significant association between the built environment and travel behavior after controlling for some preference traits was verified, establishing causality hinges on stronger conditions than the ones established in this analysis. In that sense, the next chapter elaborates on the necessary conditions to establish causality and introduces a methodology to empirically assess this relationship.

CHAPTER 5 CROSS-SECTIONAL ANALYSIS AND THE CAUSALITY PROBLEM

5.1 INTRODUCTION

Having established significant statistical associations between the built environment and travel behavior, this chapter discusses the issue of causality from a cross-sectional analysis perspective. It elaborates on the conditions of causality as well as the main limitations of cross-sectional analysis and proposes a methodology to overcome these limitations, thus providing the theoretical background for the empirical applications presented in Chapter 6 and Chapter 8.

5.2 THE CAUSAL TREATMENT EFFECT ESTIMATION PROBLEM

Framing the causality problem under a treatment effect framework, consider for now the treatment of interest *z,* defined as any measure of the built environment, and the observed outcomes Y, as any continuous or count travel behavior variable. To motivate the problem at hand, first consider a naïve hypothesis of the relationship between the built environment and travel behavior. Without going into details about magnitude and direction of effects, Figure 5-1 suggests that the effect of urbanization level on travel behavior is significant and causal.

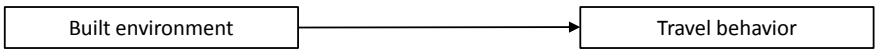


Figure 5-1 Naïve hypothesis of a causal effect between the built environment and travel behavior

For illustration purposes, further assume that the treatment variable of interest is binary (i.e. urban vs suburban), following Rubin (1977), for the *i*th individual, the average treatment effect (ATE) is defined as

$$(14) \qquad \mathrm{E}[\mathrm{y}_{1\mathrm{i}} - \mathrm{Y}_{0\mathrm{i}}] = \mathrm{E}[\mathrm{Y}_{1\mathrm{i}}] - \mathrm{E}[\mathrm{Y}_{0\mathrm{i}}]$$

In a similar manner, the average treatment effect on the treated (ATT) can be defined as

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

where Y_{1i} corresponds to observed outcome when treated and Y_{0i} to outcome when untreated, and z_i takes value 1 if treated (i.e. urban) and value 0 if untreated (i.e. suburban). However, $\mathrm{E}[\mathrm{Y}_{0\mathrm{i}}|z_i = 1]$ is not observed. That is, we do not observe the outcomes of treated individuals in the event that they were not treated, it is a counterfactual outcome. However, to the extent that the treatment is truly randomly allocated, treatment is independent from outcomes

(16) $(Y_{0i}, Y_{1i} \perp z_i)$

thus

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

so that

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

where by randomization, the average treatment effect (ATE) equals the average treatment on treated (ATT). The problem with the naïve estimator in equation (18) is that a truly random experiment of residential location is virtually impossible, and in the absence of randomization the estimated coefficients are biased and inconsistent. This can be easily seen by restating equation (15) following Angrist (1998) where

(19) $\mathrm{E}[\mathrm{Y}_{1\mathrm{i}} - \mathrm{Y}_{0\mathrm{i}}|\mathrm{z}_\mathrm{i} = 1] = \mathrm{E}[\mathrm{Y}_{1\mathrm{i}}|\mathrm{z}_\mathrm{i} = 1] - \mathrm{E}[\mathrm{Y}_{0\mathrm{i}}|\mathrm{z}_\mathrm{i} = 1] + (\mathrm{E}[\mathrm{Y}_{0\mathrm{i}}|\mathrm{z}_\mathrm{i} = 1] - \mathrm{E}[\mathrm{Y}_{0\mathrm{i}}|\mathrm{z}_\mathrm{i} = 0])$

where the component to the right side of the summation corresponds to selection bias. Tis bias cancels out if and only if treatment assignment is independent from outcomes as equation (16) shows.

Consider now, under the conditional independence assumption (CIA), that the treatment of interest is independent from the observed outcomes given a set of covariates $\mathbf{X}_i$[8]

[8] Note that we refer to Covariates as those variables that are not of direct interest for the analysis but necessary to control for.

(20) $(Y_{0i}, Y_{1i} \perp z_i | \boldsymbol{X}_i)$

Angrist (1998) showed that the average treatment effect on treated (ATT) can be estimated using a matching estimator, where by the law of iterated expectations

$$(21) \quad E[Y_{1i} - Y_{0i}|z_i = 1] = E\{E[Y_{1i} - Y_{0i}|z_i = 1, \boldsymbol{X_i}]|z_i = 1\}$$
$$= E\{E[Y_{1i}|z_i = 1, \boldsymbol{X_i}] - E[Y_{0i}|z_i = 1, \boldsymbol{X_i}]|z_i = 1]\}$$
$$= E\{E[Y_{1i}|z_i = 1, \boldsymbol{X_i}] - E[Y_{0i}|z_i = 0, \boldsymbol{X_i}]|z_i = 1]\} = E[\beta_X|z = 1]$$

With discrete covariates, a sample estimator can be obtained by weighting β_X by the treatment probability at any value of $\mathbf{X_i}$ so that

$$(22) \quad E[Y_{1i} - Y_{0i}|z_i = 1] = \frac{\sum_x \beta_x P(z_i = 1|\boldsymbol{X_i} = x)P(\boldsymbol{X_i} = x)}{\sum_x P(z_i = 1|\boldsymbol{X_i} = x)P(\boldsymbol{X_i} = x)}$$

where β_x is the difference of the mean between treated and untreated for any given value of x.

Angrist (1998) points out, however, that the main difference between regression and matching is simply the weighting scheme used to pool estimates at different values of $\mathbf{X_i}$. That is, while matching weights are proportional to treatment probability at any value of $\mathbf{X_i}$, regression weights are proportional to the treatment variance at each value of $\mathbf{X_i}$ so that

$$(23) \quad \beta_{OLS} = \frac{\sum_x \beta_x \left[P(z_i = 1|\boldsymbol{X_i} = x)\left(1 - P(z_i|\boldsymbol{X}_i = x)\right)\right]P(\boldsymbol{X_i} = x)}{\sum_x \left[P(z_i = 1|\boldsymbol{X_i} = x)\left(1 - P(z_i|\boldsymbol{X_i} = x)\right)\right]P(\boldsymbol{X_i} = x)}$$

The difference between estimates, Angrist explains, depends on how much treatment effects vary with X and on the range of values for P(z=1|**X**). He concludes that in the absence of theory that explains response to treatment, researchers should expect methods that exploit different sources of variation to produce different results. That being said, empirical evidence suggests that violations to the linearity condition might result in strong estimation bias in OLS (Imai & van Dyk, 2004), which might favor the use of matching and stratification approaches to estimate causal effects in the absence of randomization. However, as the number of covariates increases, the number of sub-classes increases exponentially, rendering many subclasses empty, or with either no control or treated units,

making impossible to draw estimates for the whole population (Corchran, 1965; Rosenbaum & Rubin, 1984).

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

5.3 THE PROPENSITY SCORE FUNCTION

The propensity score, defined as the conditional probability of treatment given observed covariates, was proposed by Rosenbaum and Rubin (1983) as a way to remove bias due to observed covariates. By acting as a balancing score in a non-randomized treatment assignment context, the propensity score makes inherently different groups comparable, the main advantage being the possibility of balancing a potentially large set of covariates $\mathbf{X}_i$ using one single scalar function.

The theoretical basis supporting the propensity score are discussed in Rosenbaum and Rubin (1983), and can be summarized into five points, which are quoted verbatim (in italics) and briefly elaborated upon (when necessary) to provide a general understanding of the approach. In that sense, note that this section borrows heavily from Rosenbaum and Rubin[9].

- *"The propensity score is a balancing score".* That is, given a binary treatment z, as a function of observed covariates the propensity score will balance $\mathbf{X}_i$, so that conditional on the propensity score function $\mathrm{P}(\mathbf{X_i}) = \mathrm{P}(\mathrm{z_i}|\mathbf{X_i})$, the distribution of $\mathbf{X}_i$ is the same for treated and untreated groups. In other words, conditional on P($\mathbf{X}_i$), $\mathbf{X}_i$ and z are independent

$$\Pr\{\mathrm{z_i}|\mathbf{X_i}, \mathrm{P}(\mathbf{X_i})\} = \Pr\{\mathrm{z_i}|\mathrm{P}(\mathbf{X_i})\} \tag{24}$$

[9] Interested readers, however, are referred to the original article for a more extensive explanation

- *"Any score that is "finer" than the propensity score is a balancing score; moreover, x is the finest balancing score and the propensity score is the coarsest."* It is the coarsest as it balances a potentially large set of covariates $\mathbf{X}_i$ using one single scalar function, which provides its empirical attractiveness.

- *"If treatment assignment is strongly ignorable given x, it is strongly ignorable given any balancing score."* Given equation (24), strong ignorability of treatment implies that outcomes (Y_{0i},Y_{1i}) are independent from treatment assignment given P($\mathbf{X}_i$). In addition, every unit has a chance to receive either treatment state

  (25) $$\mathrm{P}\{(Y_{0i}, \mathrm{Y}_{1\mathrm{i}})|\mathrm{z}_\mathrm{i}, \mathrm{P}(\mathbf{X_i})\} = \mathrm{P}\{(Y_{0i}, \mathrm{Y}_{1\mathrm{i}})|\mathrm{P}(\mathbf{X_i})\}\,; 0 < \mathrm{P}(\mathrm{z}_\mathrm{i} = 1|\mathrm{P}(\mathbf{X_i}) < 1$$

  This assumption is conceptually similar to the CIA assumption illustrated in equation (20) where the treatment of interest z is independent from observed outcomes given a set of covariates $\mathbf{X}_i$.

- *"At any value of a balancing score, the difference between the treatment and control means is an unbiased estimate of the average treatment effect at the value of the balancing score if treatment assignment is strongly ignorable. Consequently, with strong ignorable treatment assignment, pair matching on a balancing score, sub-classification on a balancing score, and covariate adjustment on a balancing score can all produce unbiased estimates of treatment effects".* In other words, the strong ignorability of treatment assumption is of crucial importance to the estimation of unbiased treatment effects.

- *"Using sample estimates of balancing scores can produce sample balance on x."*

5.3.1 Estimating the propensity score and treatment effects

Rosenbaum and Rubin (1983) note that in a randomized trial the propensity score is a known function defined by the randomization mechanism. In a nonrandomized case, however, this function is not known but can be estimated from observed data, using limited dependent variable models such

as the logit model. Care should be taken to include as much relevant covariates as possible in the specification function.

To estimate the treatment effect, several approaches have been proposed, of which the most common are matching, weighting, and stratification. The first approach is the matching approach, which is conceptually similar to the approach described in in equation (22), but matching on P($\mathbf{X}_i$) instead of $\mathbf{X}_i$. Since P($\mathbf{X}_i$) is not discrete, some strategies are necessary to match treated and untreated groups that are "close", although this "closeness" depends on the estimation method. Heckman et al. (1998) defines the average treatment effect as

$$(26) \qquad \mathrm{ATE}_{\mathrm{matching}} = N_1^{-1} \sum_{i=1}^{N} \left\{ Y_{1i} - \sum_{j \in \{z=0\}} W_{N0N1}(i,j) Y_{0j} \right\}$$

where N_0 is the number of observations in the untreated group, N_1 is the number of observations in the treated group and $W_{N0N1}(i,j)$ is a value by which Y_{0j} is weighted. Among the several matching estimators existing, the value assigned to $W_{N0N1}(i,j)$ marks the difference between one another.

Adapting Heckman et al.'s notation to the propensity score case, for the *i*th individual, given a neighborhood C(P($\mathbf{X}_i$)), and a group $\mathrm{A_i} = \{j \in z = 0 | X_j \in C(P(\boldsymbol{X_i}))\}$ that includes all units matched to the *i*th unit, for the nearest neighborhood matching estimator where

$$(27) \qquad C\big(P(\boldsymbol{X_i})\big)_{nearest} = \min_{\mathrm{j}} \{P(X_i) - P(X_j)\}, j \in \{z = 0\}$$

and the caliper matching estimator, where

$$(28) \qquad C\big(P(\boldsymbol{X_i})\big)_{caliper} = \{\mathrm{P(X_j)} | \{P(X_i) - P(X_j)\} < \varepsilon\}$$

where ε is arbitrarily defined, $\mathrm{W_{N0N1}}(i,j) = 1 \; if \; j \in A_i$, and zero otherwise. In the Kernel estimator case

$$(29) \qquad \mathrm{W_{N0N1}}(i,j) = \frac{G_{ij}}{\sum_{k \in \{z=0\}} G_{ik}}$$

where $G_{ik} = (\frac{P(X_i)-P(X_k)}{a_{N0}})$ is a kernel weighting function, and a_{N0} a smoothing parameter. In this case, $C(P(\mathbf{X_i}))_{Kernel}$ includes all values where $W_{N0N1}(i,j) > 0$.

The second approach is the weighting approach, which uses the Horvitz-Thompson estimator (Horvitz & Thompson, 1952) to estimate the expectation of the unconditional response under treatment by weighting the treated population by the inverse of the propensity score (Imbens & Wooldridge, 2008) where

$$(30) \qquad \mathrm{ATE}_{\mathrm{weighting}} = N^{-1}\sum_{i=1}^{N}\left[\frac{Y_i \cdot z_i}{P(\boldsymbol{X_i})} - \frac{Y_i \cdot (1-z_i)}{1-P(\boldsymbol{X_i})}\right] = N^{-1}\sum_{i=1}^{N}\left[\frac{Y_i \cdot \left(z_i - P(\boldsymbol{X_i})\right)}{P(X_i)\left(1-P(\boldsymbol{X_i})\right)}\right]$$

This approach, as Angrist & Pischke (2009) point out, does without the rather cumbersome matching procedures.

Finally, the stratification approach consists on sub-classifying the sample on J number of strata based on the propensity score where the ATE can be estimated as

$$(31) \qquad \mathrm{ATE}_{\mathrm{stratification}} = \sum_{j=1}^{J}\left(\bar{Y}_{j1} - \bar{Y}_{j0}\right) \cdot W_j$$

where $\bar{Y}_{j1}$ is the mean outcome in class j when treated, $\bar{Y}_{j1}$ the mean outcome in class j when untreated, and W_j is the relative weight of strata j estimated as n_j/N.

Rosenbaum and Rubin (1984) showed that a 5 strata sub-classification of the propensity score might reduce over 90% of bias due to observed covariates. Imbens & Wooldridge (2008) point out, however, that although five strata have been commonly used empirically, depending on sample size and the joint distribution of the data, fewer or more strata might results in lower mean square error.

In terms of empirical applications in the planning field, as it was discussed in Chapter 2, several studies in the transport literature have implemented propensity score methodologies as a way to address the self-selection issue. Nevertheless, polarizing the built environment to a binary treatment (usually urban vs. suburban) is a rather strong assumption that ignores the spectrum of variability in

terms of how "urban" or how "suburban" a neighborhood might be. In other words, a binary treatment considers all neighborhoods within each treatment class identical in its built environment features, thus making the estimates insensitive to variations in neighborhood compositions.

In that sense, the binary approach is adequate in the case of neighborhood to neighborhood comparisons as previous studies demonstrated but not practical for large scale analysis at the city level as the one proposed in this dissertation.

5.4 GENERALIZING THE PROPENSITY SCORE TO CONTINUOUS TREATMENTS

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

Imai and Van Dyk, also demonstrated that equations (24) and (25) can be extended to show that even for non-binary treatments, the propensity score serves as a balancing score

$$(32) \qquad \Pr\{\mathrm{T_i^A}|\mathbf{X_i}, \mathrm{P}(\mathbf{X_i})\} = \Pr\{\mathrm{T_i^A}|\mathrm{P}(\mathbf{X_i})\}$$

and that the outcome distribution given a potential treatment t^P, $Y_i(t^P)$ is independent from treatment assignment given $P(\mathbf{X_i})$

$$(33) \qquad Pr\{Y_i(t^P)|\, T_i^A, P(\boldsymbol{X_i})\} = Pr\{Y_i(t^P)|P(\boldsymbol{X_i})\}$$

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

(34) $\Pr\{Y_i(t^P)\} = \int \Pr\{\mathrm{Y_i}(\mathrm{t^P})|\mathrm{T_i^A} = \mathrm{t^P}, \theta\} \Pr(\theta)\mathrm{d}\theta.$

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

(35) $\Pr\{Y_i(t^P)\} \approx \sum_{\mathrm{j=1}}^{\mathrm{J}} \Pr_{\widehat{\phi_\mathrm{j}}}\{\mathrm{Y_i}(\mathrm{t^P})|\mathrm{T_i^A} = \mathrm{t^P}\} \cdot \mathrm{W_j}$

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

(36) $\widehat{\boldsymbol{\phi}} = \sum_{\mathrm{j=1}}^{\mathrm{J}} \widehat{\phi_\mathrm{j}} \{\mathrm{Y_i}(\mathrm{t^P})|\mathrm{T_i^A} = \mathrm{t^P}, \mathbf{X_i}\} \cdot \mathrm{W_j}$

where covariates $\mathbf{X_i}$ are included to control for variability of θ within strata. The average treatment effect is then a function of $\widehat{\phi}$; in this case, the weighted treatment coefficient of the regression of the outcome variable $Y_i(t^P)$ on t^P and all covariates, where weights are given by the sample relative weight n_j/N.

In practice, first, the propensity score function is estimated through an OLS regression of the treatment variable $\mathrm{T_i^A} = \mathrm{t^P}$ on all covariates $\mathbf{X_i}$, where the conditional mean function $\hat{\theta}_{\boldsymbol{\psi}}(\mathbf{X_i}) = \mathbf{X_i^T}\widehat{\boldsymbol{\beta}}$, characterizes the propensity score. Using our score estimate $\hat{\theta}$, that is, the regression fitted values, the sample is then stratified in approximately equal strata and the outcome variables of interest are then regressed against the same covariates $\mathbf{X_i}$ within each strata. The average treatment effect is simply the weighted average of the within-strata treatment coefficients. The variance for the weighted coefficients is estimated as

(37) $\sum_{j=1}^{J} W_j^2 \cdot Var(\hat{\beta}_j)$

where Wj is the weight of each strata j, where $\sum_{j=1}^{J} W_j = 1$.

5.5 HYPOTHESIZING THE RELATION BETWEEN TREATMENT, OUTCOMES AND COVARIATES

Having defined the conditions for causality in a cross-sectional setting, and based on the literature findings discussed in Chapter 2, and the empirical findings presented in Chapter 3 and Chapter 4, Figure 5-2 illustrates the hypothesized relation between the built environment, travel behavior and other covariates upon which the empirical analysis of subsequent chapters is based.

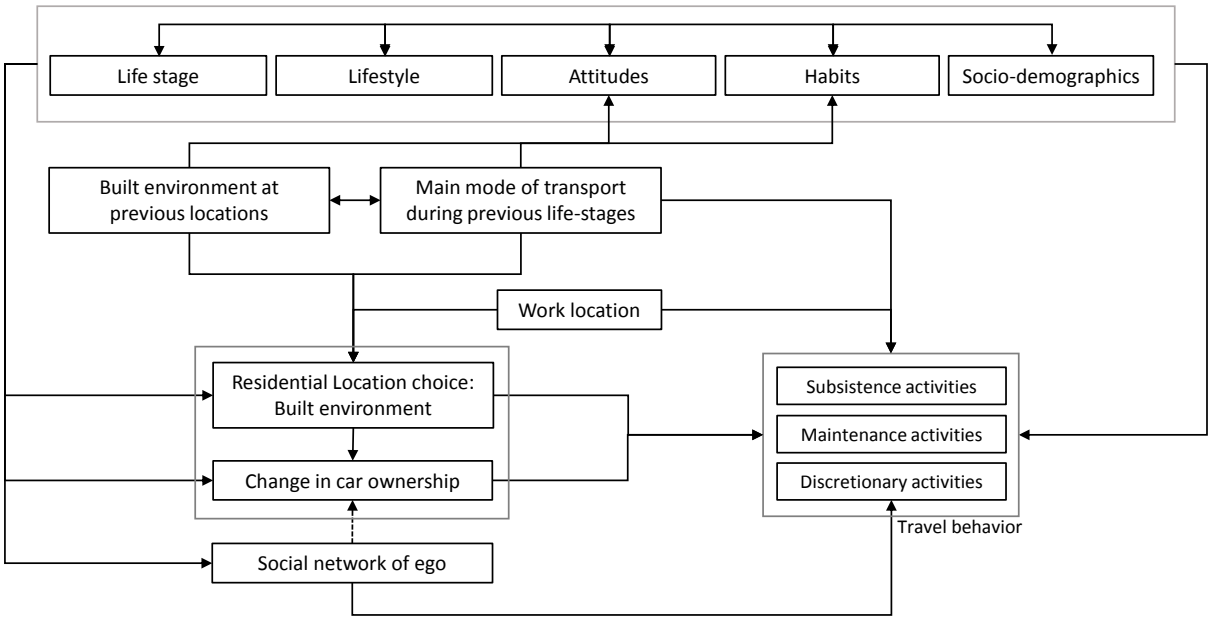


Figure 5-2 Hypothesized relation between residential location, travel behavior and covariates

Figure 5-2 also clearly illustrates the residential self-selection problem resulting from a non-random residential location choice process[10]. This process is hypothesized as an interdependent choice with changes in auto ownership levels, and a function of factors such as work location, household life stage and lifestyle, as well as transport and housing related attitudes and travel habits. In addition, it is hypothesized that the built environment characteristics at past locations and past travel behavior also influence residential location choice.

[10] Social network of ego is hypothesized to influence travel behavior of discretionary activities. This connection, however, is not addressed in this dissertation.

The observed outcomes correspond to several dimensions of travel behavior for three types of activities. Subsistence activities are defined as work and study activities. Maintenance activities refer to those activities other than subsistence activities that need to be conducted in the course of daily life such as grocery shopping, visits to the doctor, going to the bank, and other personal business. Discretionary activities refer mainly to leisure activities such as leisure shopping, eating-out, go dancing etc.

5.6 CONCLUSION

This chapter discussed the causality problem from a cross-sectional perspective. Having established the conditions for causality, a propensity score approach under continuous treatment regimes is introduced as a feasible alternative to analyze the relation between the built environment and travel behavior. The suggested method overcomes the limitations associated with polarizing the built environment to a binary treatment. Empirical applications are presented in Chapter 6 and Chapter 8.

CHAPTER 6 PROPENSITY SCORE WITH CONTINUOUS TREATMENT: AN EMPIRICAL APPLICATION IN HIROSHIMA CITY

6.1 INTRODUCTION

Following the methodology introduced in Chapter 5, this chapter presents an empirical application of the propensity score method under continuous treatments to model maintenance and discretionary trip frequencies. This application thus relaxes the binary treatment assumption (i.e. urban vs. suburban) and assumes a continuous treatment of urbanization level estimated as a latent variable. To the best of our knowledge this is the first application of its kind in the planning literature. Findings suggest that compared against the propensity score estimates, OLS might over-estimate the effect of the built environment on trip frequencies. However, both methods are consistent in suggesting the existence of a mode substitution mechanism from car to non-motorized modes given increases in the latent score of urbanization level.

6.2 HYPOTHESES STATEMENTS

The present analysis seeks to validate the following hypothesis:

- For non-work trips (maintenance and discretionary activities) there exists a mode substitution mechanism from car to non-motorized modes given increases in the urbanization level at one's residential location.

This hypothesis bears resemblance with the hypotheses put forth in Chapter 3. However, as it will be later discussed, different built environment dimensions have been combined into a single variable of urbanization level that constitutes the treatment of interest.

6.3 STUDY CHARACTERISTICS AND VARIABLE DESCRIPTION

This analysis consists of two main parts. (i) The estimation of a continuous treatment variable for urbanization level, and (ii) the estimation of its effect on travel behavior. Furthermore, given a

continuous treatment, and considering that under the Gauss-Markov assumptions the OLS estimator is the best linear unbiased estimator, the performance of the direct OLS estimates are tested against the propensity score estimates.

Data from an online survey conducted in the city of Hiroshima were used for the analysis. The survey was conducted in March 2013 through Rakuten Research, a company affiliated to Rakuten Market, the largest internet shopping site in Japan, with over 2.3 million monitors all over the country. The sample size consisted of 600 adult individuals gathered through stratified random sampling from the monitor list to match the population distribution of the 8 wards that compose the metropolitan area and the overall age distribution in the city (see Table 6-1).

Table 6-1 Hiroshima survey sample distribution given location, gender and age

	Frequency	Sample percentage	Population (2010 Census)
Population ratio by ward			
Naka ward	69	11.5%	11.1%
Higashi ward	67	11.2%	10.3%
Minami ward	61	10.2%	11.8%
Nishi ward	111	18.5%	16.0%
Asaminami ward	121	20.2%	20.2%
Asakita ward	63	10.5%	12.5%
Aki ward	37	6.2%	6.7%
Saeki ward	70	11.7%	11.5%
Gender and age			
Male	313	52.2%	48.1%
Of which: 20-29 years	47	15.0%	13.2%
Of which: 30-39 years	61	19.5%	18.8%
Of which: 40-49 years	61	19.5%	16.6%
Of which: 50-59 years	49	15.7%	14.9%
Of which: over 60 years	95	30.4%	30.2%
Female	287	47.8%	51.9%
Of which: 20-29 years	48	16.7%	12.7%
Of which: 30-39 years	62	21.6%	17.8%
Of which: 40-49 years	62	21.6%	15.3%
Of which: 50-59 years	50	17.4%	14.0%
Of which: over 60 years	65	22.6%	34.8%

Population data source: 2010 population census of Japan

Certainly, there are some issues regarding web surveys that might compromise the external validity of results, particularly the issue of coverage error, which stems from the exclusion of (i) people

who do not have access to internet and (ii) have enough digital literacy to adequately answer the questionnaire (Couper, 2000). Regarding access to the internet, the Ministry of Internal Affairs and Communications of Japan (MIC) estimated in their Communications Usage Trend Survey a penetration rate of 79.1% for 2011. A 90% penetration in the 13-49 years old cohort, and lower rates for the 60-64, 65-69, and 70-79 cohorts, with 73%, 60% and 42% diffusion rates respectively (MIC, 2012). Regarding digital literacy, the same survey estimated that among internet users, 60% used the internet for online purchases or trade of merchandise, although it noted a gap between users under 49 years old and users above that threshold. This suggests that although there is a rather high internet diffusion rate, some limitations do exist in terms of representativeness of the sample, especially for the older cohorts. At any rate, it is important to note that even if the sample is not perfectly representative of the population of interest, the main contribution of this analysis is of a methodological nature, hence the present data was considered valid for the analysis in question.

In general, the survey consisted on 3 sections, namely, individual and household attributes, attitudes and habits, and travel behavior. The next sub-sections describe the general characteristics of the gathered data.

6.3.1 Socio-demographic characteristics of the sample

Table 6-2 summarizes the socio-demographic characteristics of the sample. Compared against population characteristics, women are slightly under-represented in the sample by 4 percentage points, with a larger margin observed for women over 60 years old (See Table 6-1). Although on average online surveys are expected to be biased towards the young, the average age in the sample is also approximately five years higher than the population average for the city of Hiroshima. This might be a result of the explicit exclusion of minors (under 20 years old) from the survey. Sample households average of size was 2.66 members against the population average of 2.29, most likely a result of the underrepresentation of single households in the sample.

Table 6-2 Individual and household characteristics of Hiroshima sample

Variable	Mean	Population Mean	Std.Dev.
Household attributes		*2010 Census data*	
Household size	2.667	2.290	1.231
Single household	0.173	0.370	0.379
Pre-school children in household	0.127	-	0.333
Members over 65 years in household	0.205	0.250	0.404
Owner of detached house	0.198	0.530*	0.399
Owner of apartment	0.302		0.459
Number of drivers in household	2.420	-	0.892
Number of bikes in household	2.393	-	1.200
Number of cars in household	1.162	1.090	0.759
Household yearly income		*NTA national average*	
Income (<JPY 4,000,000)	0.326	0.592	0.469
Income (JPY 4,000,001-6,000,000)	0.283	0.232	0.451
Income (JPY 6,000,001-8,000,000)	0.164	0.095	0.371
Income (JPY 8,000,001-10,000,000)	0.117	0.041	0.322
Income (>JPY 10,000,001)	0.108	0.039	0.211
Individual Characteristics		*2010 Census data*	
Male	0.522	0.481	0.500
Age	46.835	41.500	14.487
Worker	0.532	-	0.499
Grew up in large metropolitan area (Tokyo, Osaka, etc.)	0.015	-	0.122
Grew up in the suburbs of large metropolitan area	0.047	-	0.211
Grew up in a regional city (Hiroshima, Fukuoka, etc.)	0.287	-	0.453
Grew up in the suburbs of a regional city	0.393	-	0.489
Grew up in a small city	0.143	-	0.351
Grew up in a village	0.065	-	0.247
Grew up in the remote countryside	0.050	-	0.218
Works in city center (Naka, Minami and Higashi wards)	0.412	-	0.493

**Includes both apartment and detached house owners*

Differences in household income were consistent with findings from the literature, where higher income households tend to be over-represented in web-survey samples (Couper, 2000). Compared against the Private Income Statistical Survey for 2011 (National Tax Agency, 2012), income groups under JPY 4,000,000/year are underrepresented by 44%, while the rest of the income cohorts are overrepresented. Other variables of interest, however, such as number of vehicles in the household and ratio of home-owners in the sample did not exhibit large differences from the population values.

Finally, as indicators of built environment characteristics at previous locations, respondents were ask to self-assess the type of city/town where they spent most of their childhood ranging from large metropolitan areas (i.e. Tokyo, Osaka) to villages and remote countryside.

6.3.2 Attitudes and habits

6.3.2.1 Automobile use habit

Following Verplanken et al. (1994), the Response Frequency Index (RFI) was used to measure habits in this study instead of the more traditional measures. Respondents were presented with 10 hypothetical trips and given six travel modes (Car, train, bicycle, walk, motorbike and other) to choose from. Habit was measured as the simple summation of all the times car mode was selected. Verplanken et al. noted that car choice might be determined by the general habit of car use rather than by habits with respect to a particular car trip. As a result, the RFI does not involve frequency of past behavior or retrospective introspection. In the words of Verplanken et al.:

> *"…when respondents are asked to respond to global stimuli, which are presented with a minimum of detail, there is little possibility of engaging in making elaborate tradeoffs between the pros and cons of various travel modes. Rather, we expect respondents' responses are guided by preexisting schemas about mode choice in general."*

The sample car habit mean value was 5.745 with a standard deviation of 3.214.

6.3.2.2 Attitudes towards residential location and transport

Principal component analysis (PCA) was used to estimate the factors that explain unobserved attitudes towards residential location and transport. Respondents were asked to rate on a five point Likert Scale the level of agreement with 30 statements regarding private vehicles, public transport, non-motorized modes and residential location. The questionnaire design was largely based on previous studies by Kitamura et al. (1997) and Cao et al. (2009b), adapted to the Japanese case, and

pre-tested on a convenience sample of students and faculty of the Department of Urban Engineering of the University of Tokyo.

Provided that the solution was conceptually reasonable, the number of factors was decided based on parallel analysis with 100 replications. Parallel analysis consists on generating a random dataset with the same sample size and number of indicators and comparing against the PCA estimates.

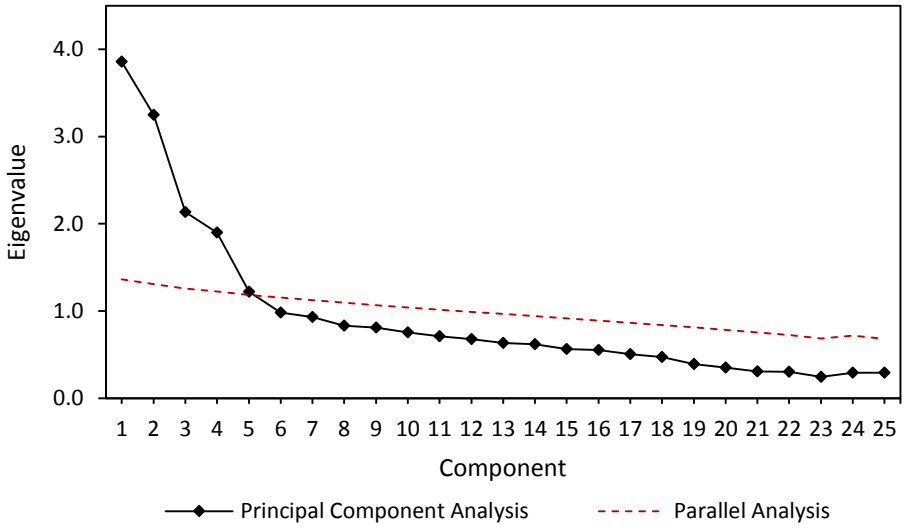


Figure 6-1 Parallel analysis of research data and random data

The rationale behind this analysis is that factors selected should account for more variance that what a factor generated from random data explains (Brown, 2006). The parallel analysis results suggested a four factor solution as illustrated Figure 6-1. This solution that is was judged conceptually feasible thus selected. The factor loadings for the four factor solution are presented in Table 6-3.

Table 6-3 Factor loadings for residential location and transport related attitudes - Hiroshima City

Factor 1: Car-dependent	**Loading**
Owning a car is a symbol of social status	.766
In general, the car is the safest transport mode	.753
I like driving	.655
Driving a car gives me a sense of freedom	.642
More roads should be built to improve traffic conditions	.561
Before giving up driving altogether, I would switch to an environmentally friendly car	.375
Factor 2: Pro-alternative modes	**Loading**
Whenever possible, I prefer walking or riding a bicycle than driving	.715
Whenever possible, I prefer riding public transport than driving	.673
I like walking	.652
I like riding a bicycle	.645
Riding the bus or the train is comfortable	.555
Using tax money to pay for public transport improvements is a good investment	.395
Gas prices should be raised as a countermeasure to traffic jams and air pollution	.387
Factor 3: Urbanite	**Loading**
Living in walking or biking range of different shops is important	.753
Living in a place with good transit accessibility is important	.744
I prefer living in a place with good access to the city center	.730
I prefer living in a place that is close to different amenities, even if I have to live in a smaller house	.539
I prefer living in a place close to a large-scale shopping center	.497
If I were to move, I would prefer moving to the city center than to the suburbs	.458
I prefer living in a place where it's easy to guarantee a parking space	.363
Factor 4: Suburbanite	**Loading**
The suburbs are a better places to raise a family than the city center	.737
I prefer living in a large house over having good transit accessibility	.657
I prefer living in a place where it's easy to guarantee a parking space	.555
As much as possible, I prefer not living in multi-family housing	.501
I prefer living in a place that is close to different amenities, even if I have to live in a smaller house	-.548
If I were to move, I would prefer moving to the city center than to the suburbs	-.643

Extraction Method: Principal Component Analysis; Rotation Method: Promax with Kaiser Normalization.
Statements translated from the Japanese. See the appendix for the original questionnaire

6.3.3 Travel behavior

The travel behavior variables considered for this analysis were home-based non-work trip frequencies by modes (maintenance and discretionary activities). Respondents were asked to state the number of home-based trips (excluding the return trip) taken during an average week by purpose and the most frequently used mode for that type of trip (See Table 6-4).

Table 6-4 Travel behavior characteristics

Variable	Mean	Std.Dev.	Minimum	Maximum
Non-work car trip frequency	2.436	3.382	0	23
Non-work transit trip frequency	0.570	1.915	0	20
Non-work non-motorized trip frequency	3.406	3.941	0	20

6.4 DEFINING THE TREATMENT OF INTEREST: URBANIZATION LEVEL AS A CONTINUOUS TREATMENT

In order to quantify urbanization level, a latent variable model was specified using confirmatory factor analysis (CFA). CFA not only allows for a complete specification of the nature of relation between the latent factor and its indicators, but also allows for the calculation of goodness of fit statistics to test how well the estimated solution reproduces the observed variances and covariances of the indicators (Brown, 2006).

Five indicators commonly associated with urban areas were specified to load on the latent variable urbanization level: population density (Figure 6-2), density of commercial facilities (Figure 6-3) average area of housing per person (Figure 6-4), ratio of households living in multifamily residences within the district (Figure 6-5), and ratio of renter households within the district (Figure 6-6). Out of the 460 districts (Chōchōmoku in Japanese) that constitute the Hiroshima metropolitan area, the effective sample size was of 400 districts. Districts with values for population or housing area equivalent to zero were excluded from the sample as these areas are not inhabited. Industrial parks in the port area were also excluded from the analysis. District socio-demographics were gathered from the 2005 national census, as the GIS data for the 2010 census was not available at the time of writing. Commercial density data was gathered from the TelPOINT pack geo-referenced phonebook, developed by ZENRIN (ZENRIN Co., Ltd, 2011). The CFA model was estimated using MPLUS 6, developed by Muthen & Muthen (2010).

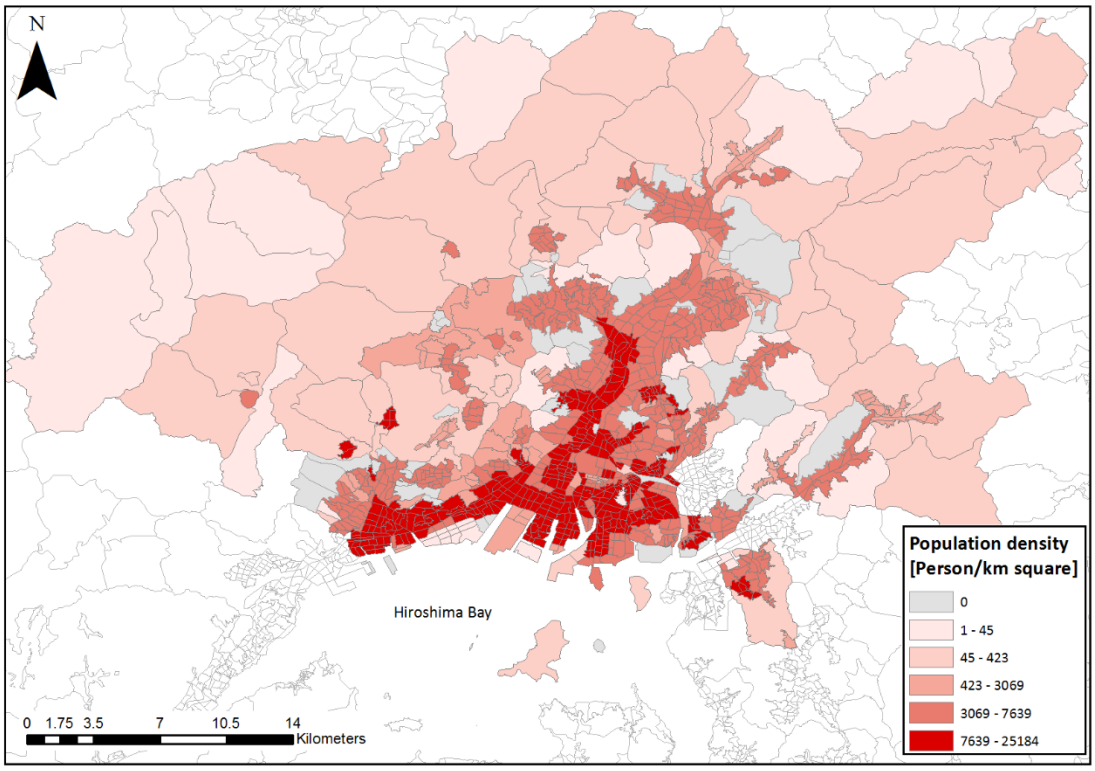


Figure 6-2 Population density map of Hiroshima City

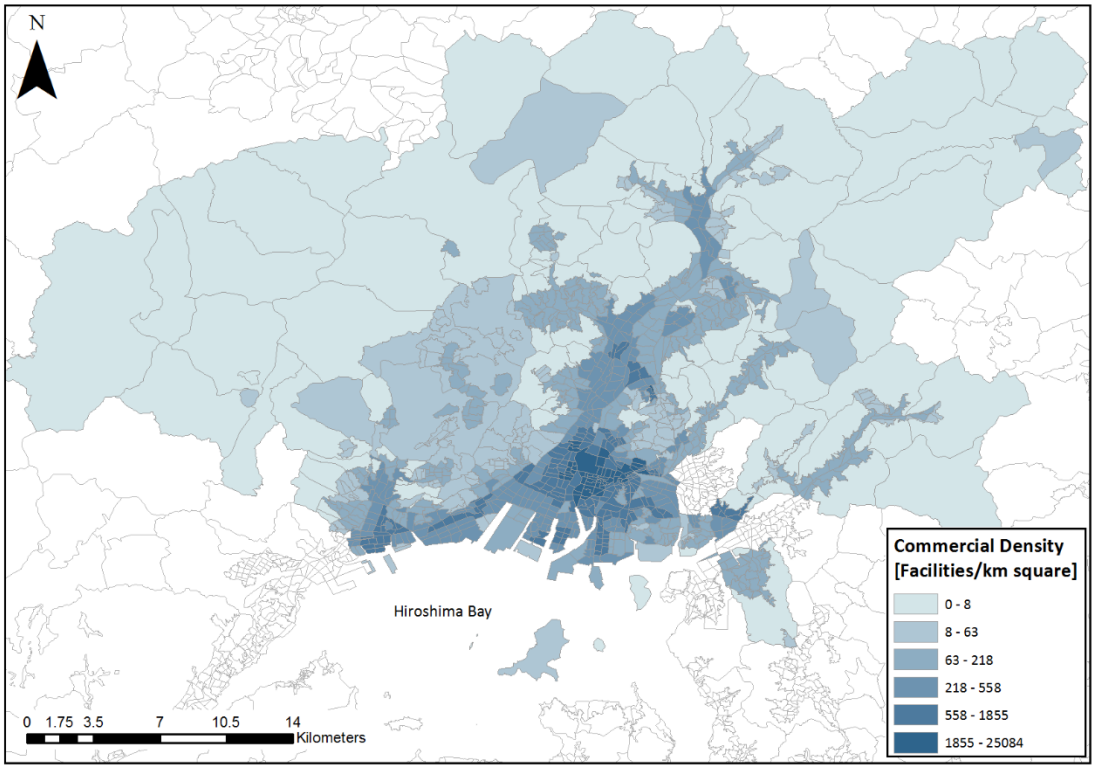


Figure 6-3 Commercial density map of Hiroshima City

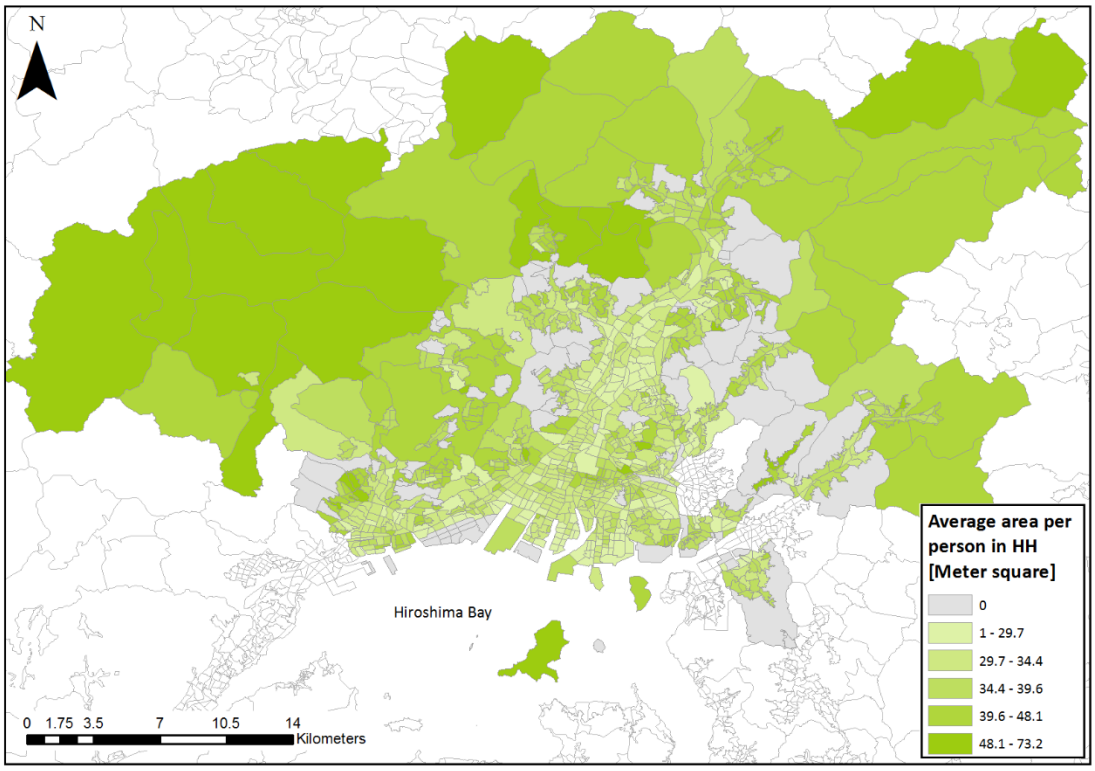


Figure 6-4 Map of average area per person in households in Hiroshima City

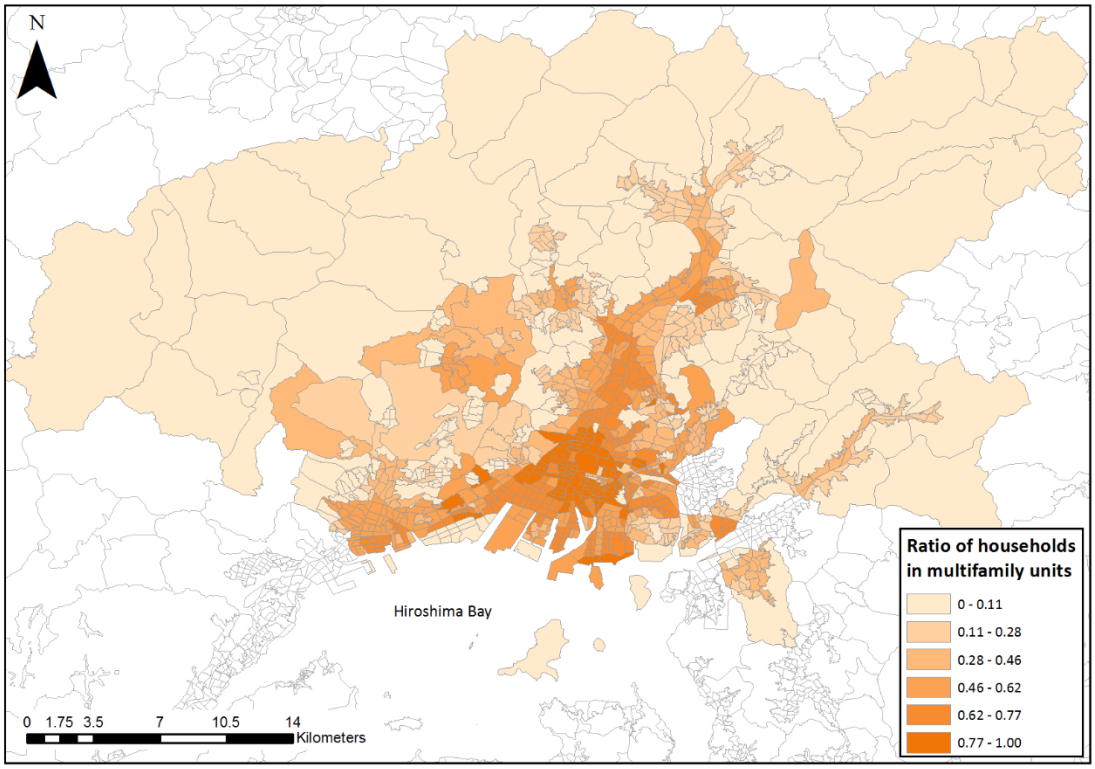


Figure 6-5 Map of ratio of households in multifamily residences in Hiroshima City

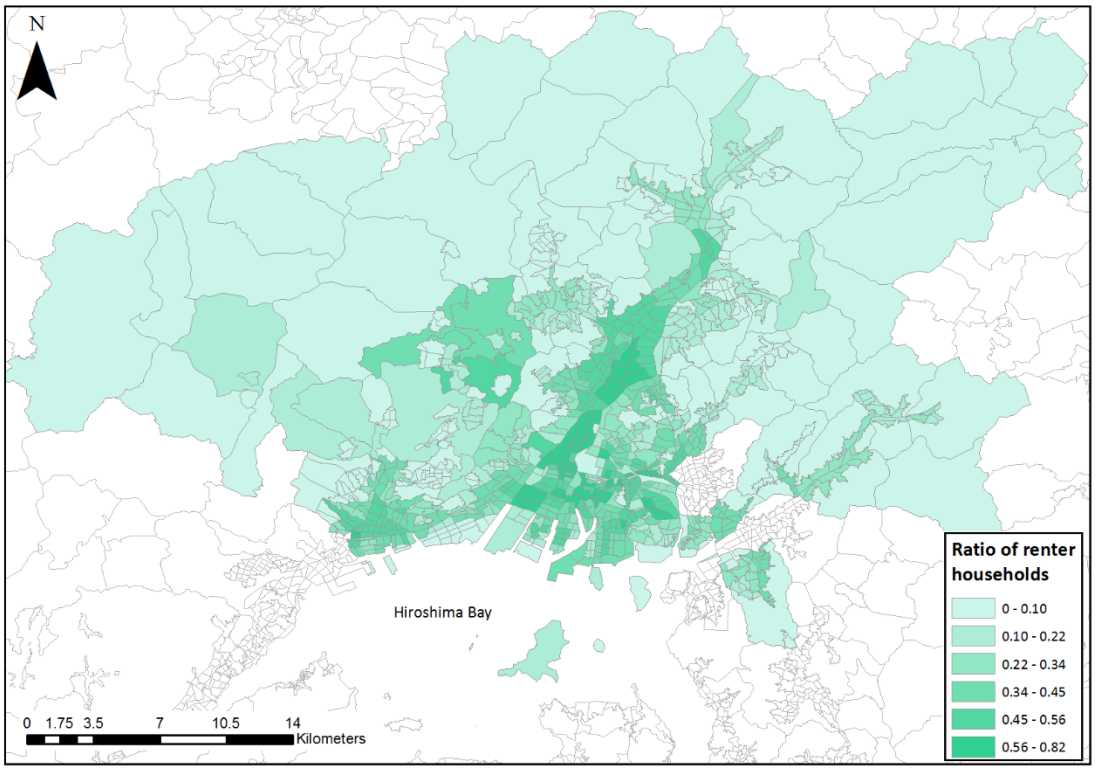
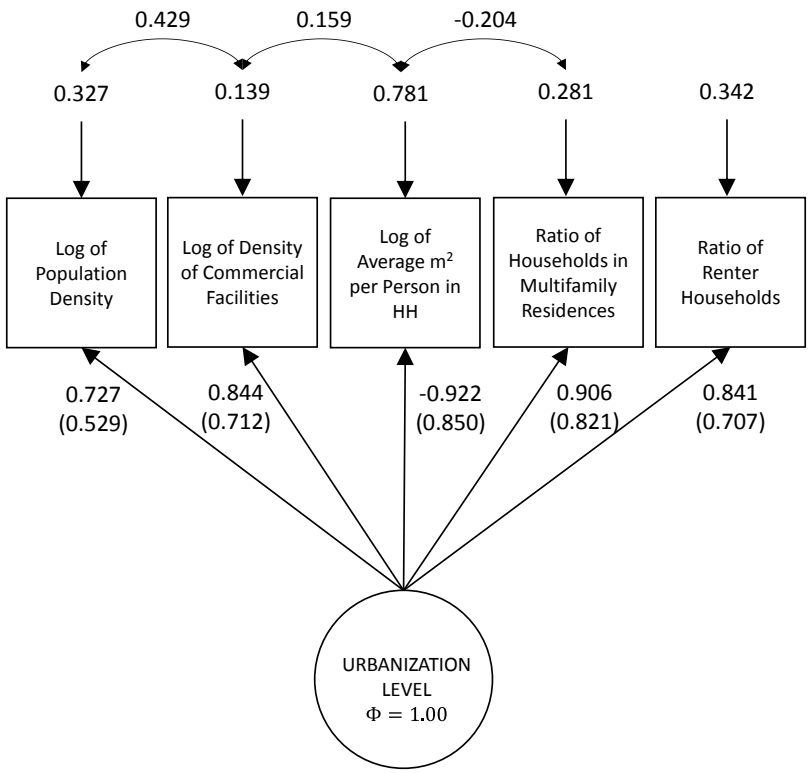


Figure 6-6 Map of ratio of renter households in Hiroshima City

Goodness of fit acceptable thresholds were guided by the values recommended by Hu and Bentler (1999) as follows: Standardized root mean square residual SRMR (≤0.08), comparative fit index CFI (≥0.95) and Tucker-Lewis index TLI (≥0.95). In terms of the Root mean square error of approximation (RMSEA) although Hu & Bentler suggested a cutoff value of ≤ 0.05, following Browne and Cudeck (1993), a cutoff value of 0.08 for the point estimate is used.

Goodness of fit indices suggest an acceptable model fit. Chi-square with two degrees of freedom was 1.813, yielding a p-value of 0.40; the lack of significance of the p-value indicates that the estimated variance-covariance matrix is not statistically different from the input matrix, thus suggesting that the model adequately reproduces observed variations in the data. RMSEA was 0.000, with a CFit value (probability RMSEA≥0.05) of 0.684. CFI and TLI were 1.000 and 1.001 respectively, while the standardized root mean square residual (SRMR) was 0.008. No modification indices were above the 3.84 threshold. Completely standardized estimated parameters are illustrated in Figure 6-7.



Chi-Square test of model fit (d.f.) 1.813 (2); p-value: 0.4040; RMSEA (C.I. 90%) : 0.000 (0.000, 0.096)
Probability RMSEA ≤.05 : 0.684; CFI: 1.000; TLI: 1.001; SRMR: 0.004
Value in parenthesis is total explained variance by the factor.
All parameter estimates are significant at the $p < 0.01$ level, except "Log of Average m^2 per Person in Household" which is significant at the $p < 0.05$ level.

Figure 6-7 Path diagram of Urbanization Level latent variable

All estimated parameters were statistically significant at the 1% level except for the coefficient for average area per person which was significant at the 5% level. Factor loading suggest that all indicators are strongly related with the latent factor urbanization level (with explained variances ranging from 0.52 to 0.85) exhibiting positive correlations with all indicators except for average housing area per person, which exhibited a negative correlation, clearly illustrating the existing tradeoff between accessibility and housing area that households face when deciding residential location.

Figure 6-8, illustrates the geographical distribution of urbanization in the city. Urbanized areas are mostly concentrated in flat areas, while the hilly areas that surround the city are less urbanized, and in most cases scantly populated. Furthermore, the monocentric nature of the city is evidenced in

the distribution of the highly urbanized areas, concentrated near the harbor and gradually dispersing away. Areas excluded from the analysis are colored in gray.

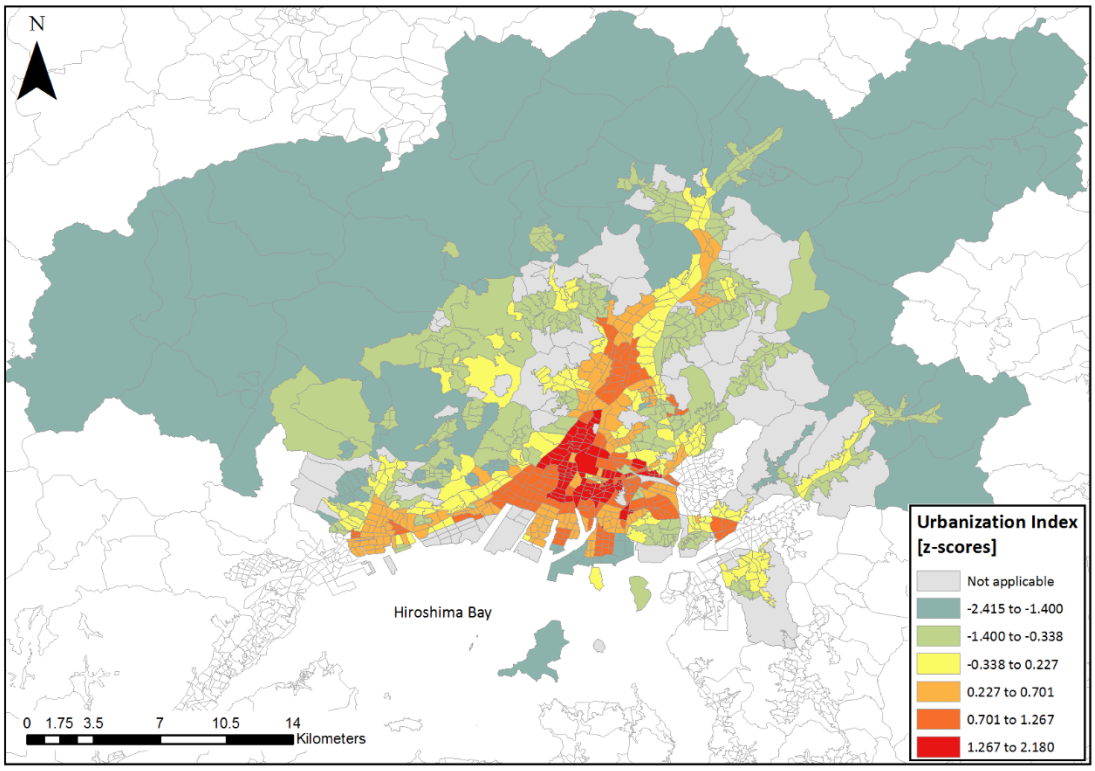


Figure 6-8 Urbanization level map of Hiroshima City

6.5 TREATMENT EFFECT ESTIMATION

6.5.1 Estimating the propensity score function

As explained in Chapter 5, an estimate of the propensity score function $\hat{\theta}$ for the continuous treatment variable urbanization level is estimated through an OLS regression. Covariate selection was based both on findings from the literature as well as theoretical considerations. Furthermore, variables that differed considerably from the population distribution, as discussed in Section 6.3 were also introduced as covariates. Estimation results are presented in Table 6-5. R-squared of the final model was 0.37 suggesting an acceptable model fit.

It is important to note that as a prediction model, the object of interest of this regression is not the individual coefficients of each explanatory variable but the scalar estimate $\hat{\theta}$, that following

the balancing score assumption balances all the covariates thought to affect treatment allocation. In that sense, the inclusion in the final model of variables that although theoretically significant might be rendered insignificant due to multicollinearity is warranted.

Table 6-5 Propensity Score OLS Estimation Results - Hiroshima City case study

N	517	S.E. of e		0.621	
Parameters	20	R-square		0.385	
d.f.	496	Adjusted R-square		0.357	
RSS	191.80	F test (p-value)		15.34 (0.000)	
Variable		**Coefficient**	**S.E.**	**t stat.**	**P value**
Constant		**0.767**	**0.189**	**4.051**	**0.000**
Age (x 10)		-0.001	0.003	-0.046	0.964
Male		-0.097	0.058	-1.665	0.096
Household size		**-0.115**	**0.034**	**-3.425**	**0.001**
Single household		**-0.183**	**0.093**	**-1.966**	**0.049**
Children in preschool /elementary school		**-0.086**	**0.050**	**-1.717**	**0.086**
Members over 65 in HH		**0.093**	**0.021**	**4.395**	**0.000**
Number of cars		0.062	0.096	0.648	0.517
Number of bicycles		**0.125**	**0.075**	**1.661**	**0.097**
Middle income (US$40,000~100,000)		0.032	0.067	0.469	0.639
High income (>US$100,001)		0.139	0.097	1.438	0.151
Car habit		**-0.039**	**0.013**	**-3.062**	**0.002**
Grew up in large city or regional city		-0.091	0.084	-1.089	0.276
Grew up in large or regional city suburbs		-0.113	0.080	-1.408	0.159
Grew up in the country side or village		**-0.339**	**0.112**	**-3.032**	**0.002**
House owner		**-0.288**	**0.061**	**-4.682**	**0.000**
Job located in city center		**0.250**	**0.058**	**4.277**	**0.000**
Attitudes: Urbanite		**0.055**	**0.028**	**1.919**	**0.055**
Attitudes: Suburbanite		**-0.167**	**0.031**	**-5.458**	**0.000**
Attitudes: Car dependent		-0.033	0.030	-1.118	0.263
Attitudes: Pro-alternative modes		-0.002	0.031	-0.073	0.941

To verify the balancedness of covariates given the estimated propensity score $\hat{\theta}$, as suggested by Imai and Van Dyk (2004) each covariate was regressed against the original treatment variable; the same regressions were run a second time but this time conditioning on $\hat{\theta}$. OLS was used for continuous covariates while binary logit was used for dummy covariates. As Figure 6-9 illustrates, without controlling for $\hat{\theta}$, most covariates are strongly correlated with the treatment, but once conditioned on the propensity score, this correlation is considerably reduced, evident in the drop of the t-statistics for each covariate.

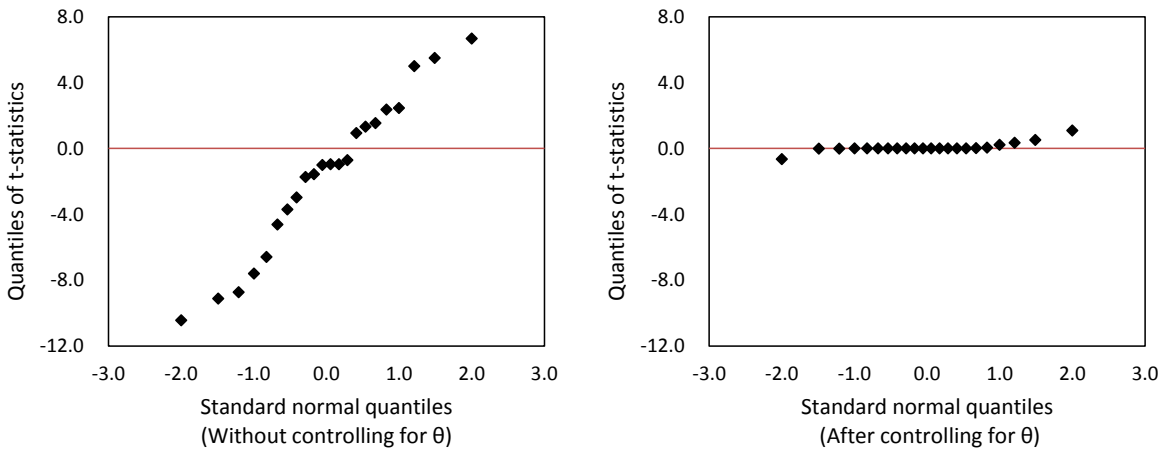


Figure 6-9 Standard normal quantile plots of t-Statistics of covariates with and without controlling for the propensity score estimate

6.5.2 Estimating the urbanization level treatment effect

Having verified that the estimate $\hat{\theta}$ balances observed covariates, the average treatment effects of urbanization level on the outcome variables of interest were estimated, outcomes being non-work car trip frequency and non-work non-motorized trip frequency. All dependent variables were introduced in the models in log form. As Table 6-6 illustrates, the sample is stratified on $\hat{\theta}$ into roughly equal sub-classes *j.* Effect estimates are compared not only against OLS estimates but against the no-covariates estimates as well. The sensitivity of estimates to stratification is tested by estimating treatment effects given different *j,* thus, sample is stratified into three, five and ten strata.

In general, all models support the hypothesis that higher urbanization levels have a negative effect on car trip frequency, and a positive effect on non-motorized trip frequency. However, the propensity score models, in particular those controlling for all covariates yield smaller effect magnitudes in most cases, suggesting that direct estimations (both with and without covariate control) tend to overestimate the real effect of the built environment on trip frequency for both modes.

In the case of car trip frequency, while the naïve estimate (no stratification, no covariates) stands at -0.39, that is, a 39% reduction in car trips given a standardized unit increase in urbanization

level, stratified full model estimates (all covariates) range from -0.21 in the three strata estimate to -0.16 in the ten strata estimate. In the case of non-motorized trips, the naïve estimate stands at 0.38, suggesting a 39% increase in walking and biking trips given a one unit increase in the urbanization level index, while stratified full model effects range from 0.26 to 0.28, for the three strata and the ten strata estimates respectively.

Table 6-6 Estimation results of causal effects of urbanization level on travel behavior in Hiroshima City

Model			**OLS**	**3 Strata**	**5 Strata**	**10 Strata**
Car trip frequency model	**N.C.**	β	-0.390	-0.211	-0.166	-0.155
		t-Stat	-8.847	-3.727	-2.894	-2.888
	A.C.	β	-0.182	-0.143	-0.118	-0.149
		t-Stat	-3.796	-2.945	-2.225	-2.860
NMM trip frequency model	**N.C.**	β	0.392	0.299	0.253	0.257
		t-Stat	7.739	4.565	3.636	3.748
	A.C.	β	0.239	0.257	0.221	0.287
		t-Stat	4.114	4.573	3.751	4.126

Certainly, given the fact that both the true propensity score, as well as the true population parameter for the treatment of interest are unknown, the misspecification issue is a non-trivial one. In spite of including a diverse range of covariates into the estimation of the propensity score function, and verifying the balance of covariates after conditioning on $\hat{\theta}$, model misspecification is still possible. Results suggest, however, that propensity score models are rather robust to model misspecifications, particularly as the number of strata *j* increases. That is, estimate ranges between no covariate models and full covariate models for each stratification scheme get smaller as number of strata increases.

In terms of limitations of the present analysis, two potential pitfalls are identified. The first one is the modifiable areal unit problem (MAUP). MAUP is a pervasive problem both in term of the way spatial zones are divided (census tracts, postal codes, etc.) and the way these zones are aggregated for analysis (Fotheringham & Wong, 1991). Given that the spatial unit of analysis is the district (Chōchōmoku in Japanese), results might be sensitive to changes in the spatial units or its aggregation scale, which are in general defined rather arbitrarily.

The second potential pitfall refers to the performance of the propensity score against OLS. The assumption that the propensity score indeed reduces bias against OLS is based on empirical findings from non-transportation literature (Rosenbaum & Rubin, 1984; Imai & van Dyk, 2004). In that sense, methodological validation through simulation using transportation data might prove a good strategy to support the findings presented in this analysis.

6.6 DISCUSSION OF FINDINGS

Regarding the implication of estimated results, empirical findings suggest the existence of a mode substitution mechanism between car and non-motorized modes as a result of increases in urbanization levels as measured by the estimated latent variable. These findings support the arguments of advocates of compact cities as ways to reduce car dependency and promote travel by alternative modes.

The presented methodology helps overcome some of the limitations of existing program evaluation approaches in the transportation literature, particularly the binary treatment assumption, which usually polarizes the built environment into two extremes (either urban or suburban), disregarding the large variability in district characteristics within cities. A continuous urbanization level treatment, as the one presented here allows thus for a more precise understanding of the built environment effect on travel behavior at all levels of the urbanization spectrum without the need to arbitrarily draw a defining line between “urban” and “suburban” which binary treatment models might be highly sensitive to. Instead, the CFA estimation of a latent variable score for urbanization level allows for the calculation of goodness of fit statistics to evaluate the estimated solution and provides statistical support to the proposed index.

It is important to highlight yet again the importance of the strong ignorability of treatment assumption. That is, the assumption that the distribution of treatment outcomes are independent from the distribution of treatment assignment conditional on the propensity score. This assumption is crucial for establishing causality. In practice, however, it is impossible to know how well does the

estimated function approximates the true population function. That being said, in order to estimate the propensity score function, variables largely cited in the literature as relevant to residential location were introduced in the model; hence, it is assumed that the estimated function is a good estimate of the true unknown function.

Finally, two potential pitfalls were identified. First, In terms of the urbanization level treatment, the first limitation is related to the modifiable areal unit problem (MAUP) where results might be sensitive to changes in the spatial unit of analysis both in terms of spatial segmentation and aggregation. Second, although the propensity score performance in bias reduction is supported by empirical evidence from non-transportation studies, methodological validation through simulation might prove a good strategy to support the findings presented in this analysis.

The limitations discussed here are the main subject of the subsequent chapters, where the treatment variable estimation model is improved and the performance of the propensity score method is simulated and validated.

CHAPTER 7 IMPROVEMENT OF THE URBANIZATION LATENT CONSTRUCT

7.1 INTRODUCTION

In Chapter 6, an empirical application of the propensity score method under continous treatment was presented. However, several limitations were identified in terms of the treatment variable estimation model. This chapter uses data from Fukuoka City to propose an improved model to estimate the urbanization latent construct. The new model addresses the modifiable areal unit problem (MAUP) by using as the spatial unit of analysis a regular sampling aggregation scheme instead of the existing political districts. In addition, a sensitivity analysis is conducted to test how sensitive results are to scale aggregation. Although parameter estimation seems to be rather robust to aggregation scales, some goodness of fit statistics deteriorate as the scale of aggregation increases, thus favoring the more dissagregate models.

7.2 ADDRESSSING THE MODIFIABLE AREAL UNIT PROBLEM (MAUP)

The Modifiable areal unit problem (MAUP) is a pervasive yet widely ignored problem in spatial analysis, stemming from the way spatial data is aggregated, both in term of zoning and scale. That is, the way spatial zones are divided (census tracts, postal codes, etc.) and the way these zones are combined for analysis. Fotheringham & Wong (1991) argued that in multivariate analysis, the effects of MAUP are essentially unpredictable. Certainly, as in the case of the analysis presented in Section 6.4, spatial zones in widely used datasets such as the national census are defined rather arbitrarily, and do not respond to any optimal zoning system, should there be any. How sensitive are estimated results to changes in terms of zoning and scale is thus a non-trivial problem.

Empirical research, however, has shown that a regular aggregation scheme such as a rectangular tessellation tends to produce more tractable results than aggregation on census geographic units (Putman & Chung, 1989; Zhang & Kukadia, 2005). Accordingly, to address the zonal

problem, instead of the existing political district divisions, a regular sampling scheme is implemented. A 300m wide hexagon (150m from the center to any vertex) tessellation was used to subdivide the city area in regular spatial units. Although more common in ecological modelling, a hexagonal grid was selected as it presents some advantages over the rectangular grid such as a better match in Euclidian distance measurements, and greater clarity in visualization (Birch, et al., 2007).

Regarding the aggregation scale problem, as suggested by Jelisnki & Wu (1996) and Dark & Bram (2007) a sensitivity analysis was conducted in order to analyze how sensitive results are to variations in the scale of analysis. Therefore, in addition to the 300m wide hexagon, three additional scales were used for the sensitivity analysis; 100m, 600m and 1000m wide hexagons.

7.3 DEFINITION OF INDICATOR VARIABLES FOR THE IMPROVED MODEL

In urban economics, combination of factors such as resource and transport advantage, economies of scale, and preference for variety in consumption and production are commonly agreed to give way to the urban aglommerations (Fujita, 1989). A myriad of factors such as land use allocation, land rent prices and population density are usually defined as functions of distance from the city center (Alonso, 1964; Mills, 1967; Fujita, 1989), while more recently in urban planning and transportation studies, particular attention has been given the the issue of accessiblity[11], as determined by the spatial distribution of potential destinations, its attractiveness and their ease of reach (Handy & Niemeier, 1997; Handy & Clifton, 2001).

Guided by urban economics and planning theory, a monocentric city would thus exhibit at its center higher access to goods and services (both in term of supply and ease of access), higher land use intensity and higher land prices, decreasing as one moves away from the center. Put another way, the closest to the city center, the higher the urbanization level. As such, for the purposes of this analysis urbanization level is conceptualized as a latent construct that accounts for the observed spatial

[11] Distance from the CBD can be understood as a simplified measure of access. Alonso (1969) notes that distance can be measured directly and does not imply subjective patterns of preferences like accessibility.

distribution of the city in terms of supply of goods and services , land use intensity, transport mobility and land prices. Indicators were selected based on the results of an exploratory factor analysis (EFA) conducted on a set of potential indicators theoretically associated with urbanization levels. In addition, the spatial data used for this analysis (with the exception of population density) has the advantage of being available in the form of point data, which allows for a flexible definition of the analysis unit in order to address the MAUP issue discussed earlier.

7.3.1 Commercial Kernel density

Using location data of commercial facilities extracted from the geo-referenced phonebook data provided by ZENRIN Co., Ltd (2011), a Kernel density of all non-industrial services was estimated via *ArcGIS*, as a measure of supply of goods and services. As defined by Silverman (1986), the multivariate Kernel estimator can be written as

$$(38) \qquad \hat{f}(x) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left\{\frac{1}{h}(\boldsymbol{x} - \boldsymbol{X}_i)\right\}$$

where *n* is the sample size, *h* is the bandwidth or smoothing parameter, and *K* is a Kernel weighting function, defined for a bivariate variable **x** following Silverman (1986) as

$$(39) \qquad K(x) = \begin{cases} 3\pi^{-1}(1 - \boldsymbol{x}^{\intercal}\boldsymbol{x})^2 & if\ \boldsymbol{x}^{\intercal}\boldsymbol{x} < 1 \\ 0 & otherwise \end{cases}$$

A symmetrical density function is drawn on each data point (each commercial facility) following the specified Kernel weighting function in equation (40) extending up to the defined bandwidth *h* at which point the weight becomes zero. The kernel density is thus the sum of these density values at each sampling point where the sampling mesh size was set at 50m x 50m. Figure 7-1 shows the Commercial density map of Fukuoka city.

Bandwidth *h* was defined rather arbitrarily at 500 meters. Nevertheless, estimated density values at bandwidths of 500 meters, 750 meters and 1,000 meters yielded high correlations, with all coefficients above 0.95. In that sense, since CFA aims at reproducing the observed variances and covariances of the data, the bandwidth specification is of little concern for the purposes of this analysis.

7.3.2 Population density

Population density was used as a measure of land use intensity. Since data from the 2005 national census was used (PASCO, 2005), at its finest resolution, the data is available only at the district level, as a result, it not possible to control for the zoning effect in the data. The distribution of population density in Fukuoka city is illustrated in Figure 7-2. Grey areas denote areas where population was zero, largely corresponding to uninhabited tracts such as parks, industrial areas or the Fukuoka airport, which are excluded from the analysis.

7.3.3 Weekday transit frequency

Weekday transit frequency was used as a measure of transport mobility. Railway data was gathered from publicly available service timetables from each operator (Fukuoka City Transport Bureau, 2014; JR Kyushu, 2014; JR West, 2014; Nishi-Nippon Railroad Co., Ltd, 2014) while bus data was provided by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT, 2011a; MLIT, 2011b). Weekday transit frequencies for locations within 800 meters from train stations, and 300 meters from bus stops were calculated and added, resulting in a single transit accessibility index as shown in Figure 7-3.

7.3.4 Land prices

Land price data was provided by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT, 2013a; MLIT, 2013b) .As illustrated in Figure 7-4 Land prices were interpolated from 1,965 data points extracted from the combined datasets via *ArcGIS* using the nearest neighbor method.

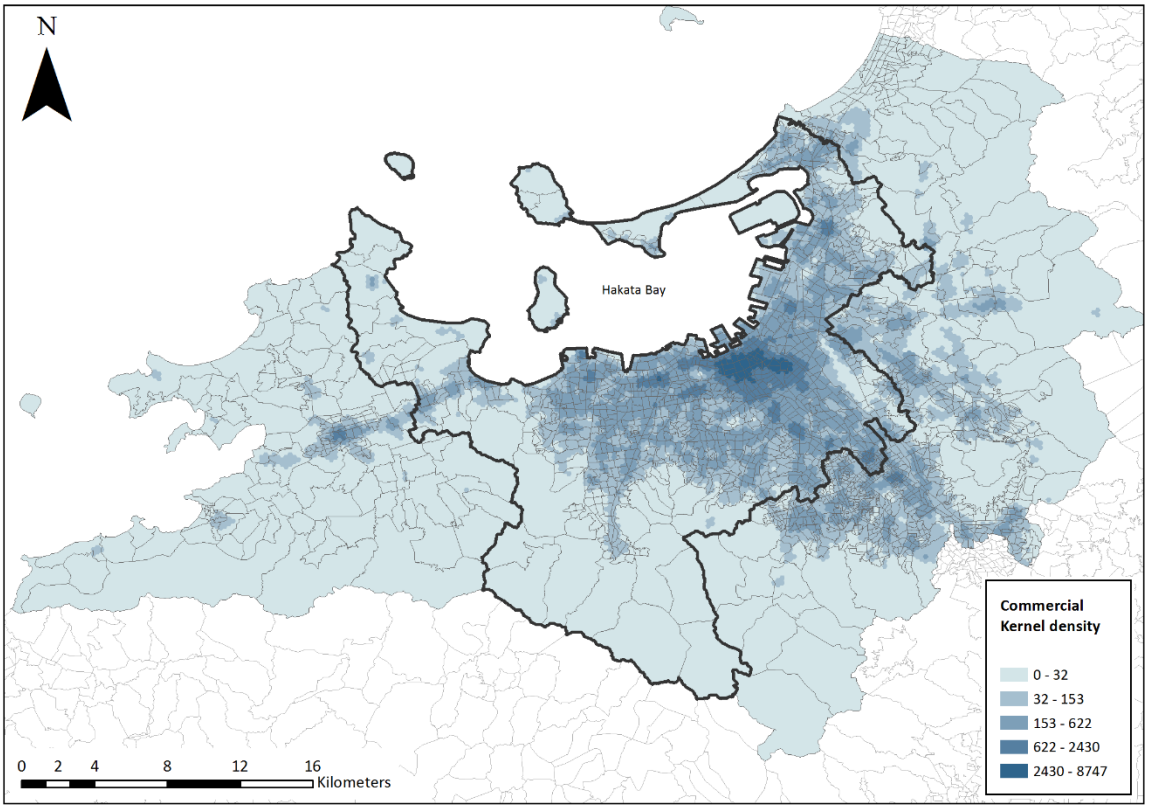


Figure 7-1. Commerce Kernel density map of Fukuoka City

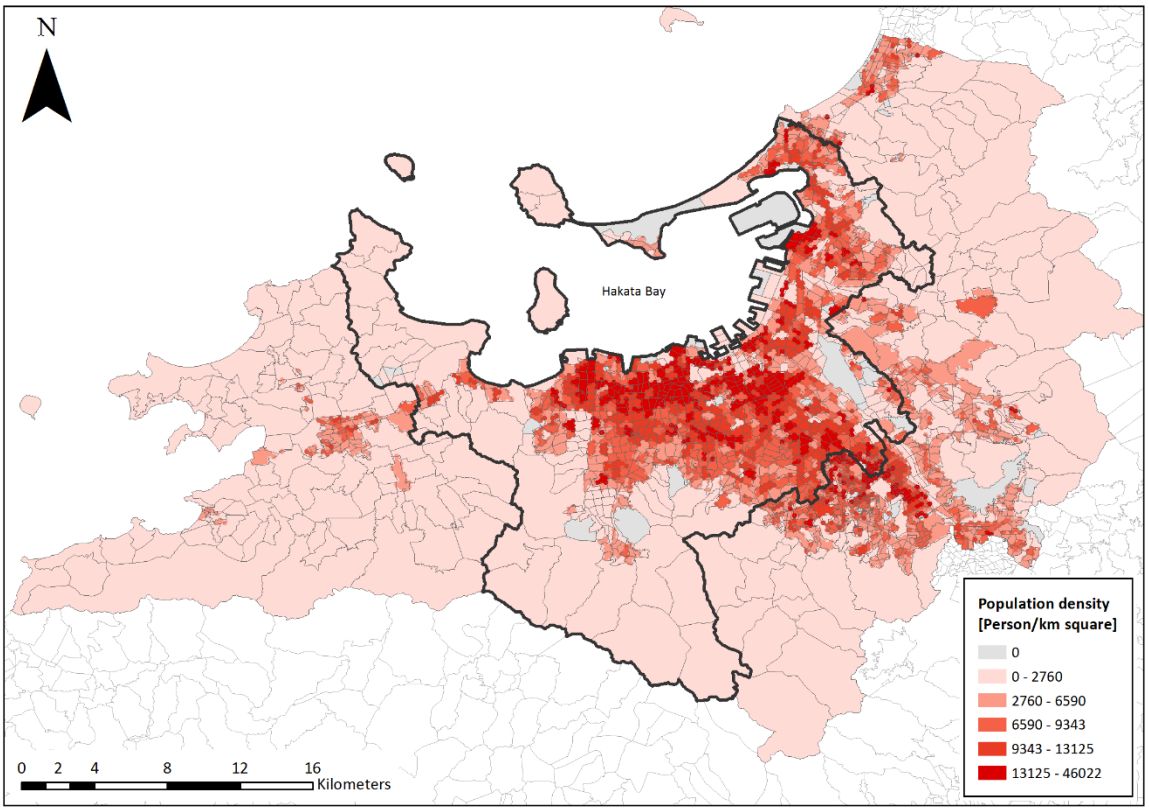


Figure 7-2. Population density map of Fukuoka City

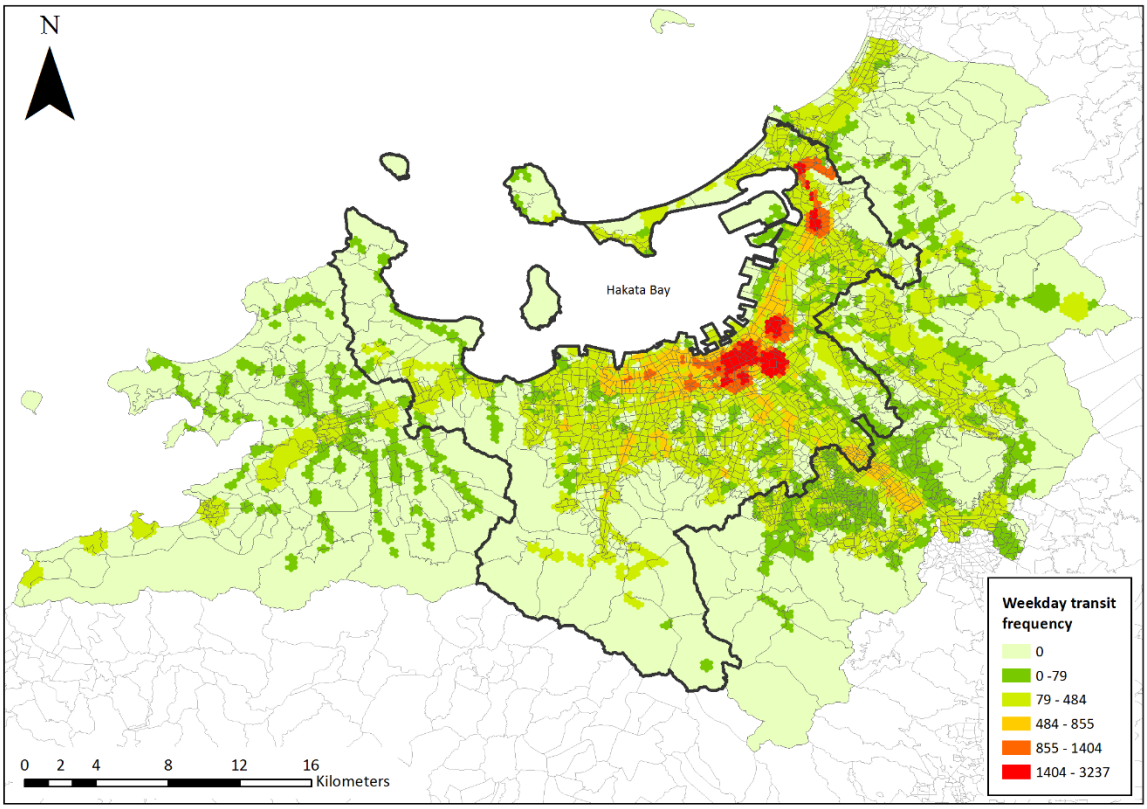


Figure 7-3. Weekday transit frequency map of Fukuoka City

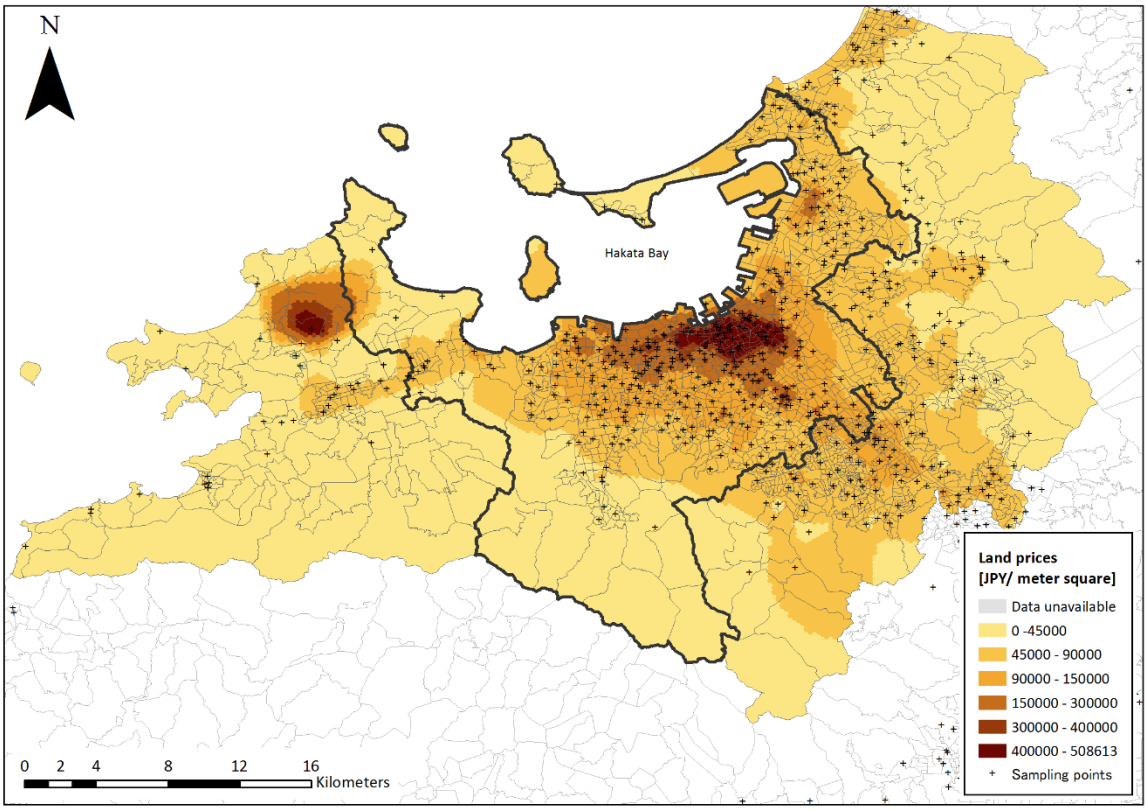


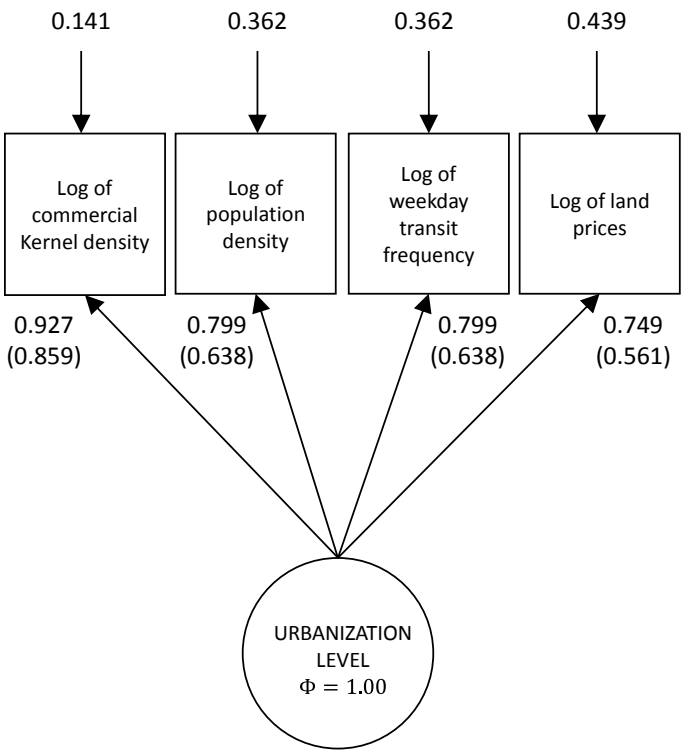
Figure 7-4. Land price map of Fukuoka City

7.4 MODEL SPECIFICATION AND RESULTS

The CFA model was estimated using MPLUS 6, developed by Muthen & Muthen (2010). Units were excluded from the analysis if (i) the population density at any given unit is equal to zero, or (ii) data for any of the indicator variables is not available for a given unit. This yielded an effective sample size of 18,485 cells out of the total 19,686 cells in which the study area was tessellated.

As a result of the multivariate non-normality condition of the indicator variables (i) all variables were introduced in their log form, and (ii) the robust maximum likelihood estimator was used. Although the issue of goodness of fit statistics remains still a hotly debated subject (Marsh, et al., 2004; Saris, et al., 2009; Heene, et al., 2011) Goodness of fit acceptable thresholds are guided by the values recommended by Hu & Bentler (1999) as follows: Standardized root mean square residual SRMR (≤0.08), comparative fit index CFI (≥0.95) and Tucker-Lewis index TLI (≥0.95). In terms of the Root mean square error of approximation (RMSEA) although Hu & Bentler suggested a cut-off value of ≤ 0.05, following Browne and Cudeck (1993), a cut-off value of 0.08 for the point estimate is used.

With 2 degrees of freedom, the Chi-square statistic is significant at the 0.01 level. This might suggest that the model does not reproduce the observed variances and covariances of the indicators well enough; nevertheless, Chi-square is inflated by sample size, thus tending to routinely reject large sample size solutions (Brown, 2006). Other indices not sensitive to sample size, however, suggest an acceptable model fit. RMSEA is 0.037, with a confidence interval of 0.028 and 0.046 at its lower and upper boundaries respectively; its upper boundary being below the cut-off value even by the stricter 0.05 threshold suggested by Hu & Bentler (1999). CFI and TLI are 0.999 and 0.996 respectively, while the standardized root mean square residual (SRMR) is 0.005. The path diagram of the estimated latent variable is shown in Figure 7-5.



Chi-Square test of model fit (d.f.) 51.38 (2); p-value: 0.000; RMSEA (C.I. 90%) : 0.037 (0.028, 0.046)
Probability RMSEA ≤.05 : 0.994; CFI: 0.999; TLI: 0.996; SRMR: 0.005
Value in parenthesis is total explained variance by the factor.
All parameter estimates are significant at the $p < 0.01$ level.
Due to multivariate non-normality, estimator is Robust Maximum Likelihood.

Figure 7-5. Path diagram of "Urbanization Level" latent variable

As illustrated in Table 7-1, 4 modification indices above the 3.84 threshold are reported. In general, modification indices above the 3.84 level suggest areas of strain in the model or potential improvements, but since modification indices reflect Chi-square changes given freely estimating the error covariances they are also sensitive to large sample sizes. Fit-improving specification search guided by a sound theoretical reasoning is a widely accepted practice in the CFA field, and given the complexity of spatial dynamics, arguments can be put forth to support this approach. That is, the theory that other sources of covariation other than the urbanization latent factor exist among indicators (as in the Hiroshima model specification) is not at all unrealistic. However, in the absence of a well-established error theory to guide these specifications the current more parsimonious model was selected with error measures (unique variances) assumed random.

Table 7-1. Model modification indices

With statements	Modification index	E.P.C.	STD E.P.C.
Log of population density with log of Kernel density	9.714	-0.069	-0.068
Log of transit frequency with log of Kernel density	19.278	-0.105	-0.095
Log of transit frequency with log of population density	51.760	0.144	0.081
Log of land price with log of Kernel density	51.744	0.048	0.127
Log of land price with log of population density	19.230	-0.026	-0.044
Log of land price with log of transit frequency	9.714	-0.020	-0.031

E.P.C.: Expected parameter change; STD E.P.C.: Fully standardized expected parameter change

All estimated parameters were statistically significant at the 1% level. Factor loadings suggest that all indicators are strongly related with the latent factor urbanization level, especially the log of commercial density, whose total explained variance stands at 85.9%. Figure 7-6 illustrates the spatial distribution of the estimated urbanization level latent variable. Clearly, there is a marked mono-centricity in the spatial distribution of the city, with the highest levels of urbanization concentrated mainly around Chuo ward and spreading outwards.

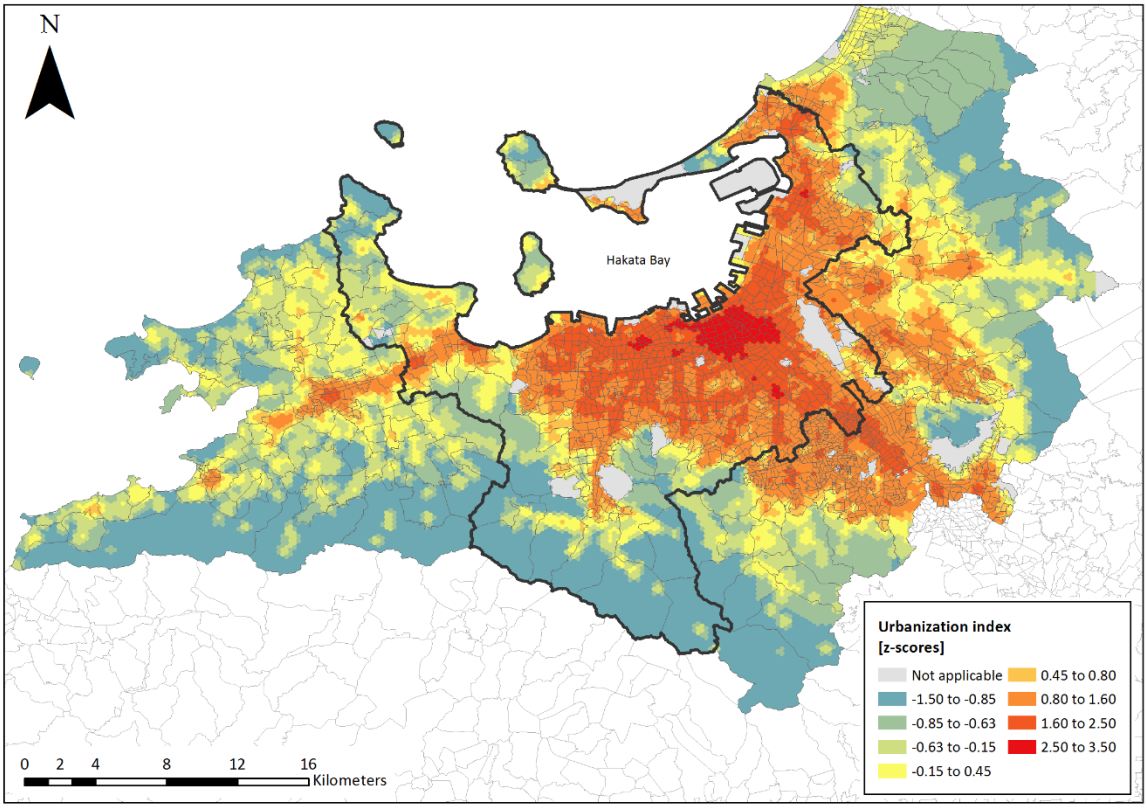


Figure 7-6. Urbanization level map of Fukuoka city

7.5 SENSITIVITY ANALYSIS TO SCALE OF AGGREGATION

As discussed earlier, a sensitivity analysis was conducted at different levels of aggregation to evaluate the robustness of results to changes in the scale of data aggregation. In addition to the present model, the same CFA analysis was conducted at three different aggregation levels with tessellations of 100m, 600m and 1000m diameter hexagons.

Table 7-2 summarizes the sensitivity analysis results. Estimated parameters are quite similar among models regardless of the scale of aggregation. On the one hand, this might suggest robustness to scale changes, on the other hand, goodness of fit indices might suggest otherwise. In the 1000m model, the RMSEA point estimate goes above the cutoff value of 0.08, while in both the 600m and 1000m models the upper bounds of the RMSEA confidence intervals also go above the set threshold. Judging strictly by goodness of fit criteria, this might suggest the rejection of these two models, but at the same time, this brings up an important question regarding the power of these statistics to detect model misspecifications. In particular, one of the main criticism to the use of cut-off values is that these values depend on conditions that are not always under the control of the researcher (Heene, et al., 2011). Marsh et al. (2004) points out that interpretations of degree of misspecifications should be evaluated in relation to theoretical issues that are likely idiosyncratic to a particular study, which further complicates things, given the lack of similar studies in the spatial analysis literature.

Although at this point the aggregation level cannot be pinpointed as the only reason for the apparent lack of fit in these models, referring back to the MAUP issue, Fotheringham & Wong (1991) had suggested using disaggregate data whenever possible to avoid the MAUP altogether. Although this is in many cases a difficult compromise, a good heuristic guiding model selection might be to use data as disaggregate as possible and submit these models to goodness of fit tests and other theoretical considerations.

Table 7-2 CFA sensitivity analysis at different levels of aggregation

	100m Hexagon grid			300m Hexagon grid*		
Sample size	167721			18485		
Chi-Square test						
Value (d.f.)	252.711	(2)		51.38	(2)	
p value	0.000			0.000		
RMSEA (Root Mean Square Error of Approximation)						
Estimate	0.036			0.037		
90% C.I.	(0.032-0.040)			(0.028-0.046)		
Probability RMSEA ≥ .05	0.999			0.994		
CFI/TLI	CFI: 0.999	TLI: 0.997		CFI: 0.999	TLI: 0.996	
SRMR (Standardized Root Mean Square Residual)						
Value	0.005			0.005		
Fully standardized results						
Coefficients	**Estimate**	**S.E.**	**t stat.**	**Estimate**	**S.E.**	**t stat.**
Log of commerce Kernel density	0.955	0.001	1209.433	0.927	0.002	374.329
Log of population density	0.816	0.002	487.883	0.799	0.004	218.165
Log of weekday transit frequency	0.784	0.002	434.815	0.799	0.004	202.212
Log of land price	0.792	0.001	530.516	0.749	0.005	150.17
Intercepts						
Log of commerce Kernel density	0.933	0.003	367.789	0.957	0.006	160.902
Log of population density	2.220	0.005	473.71	2.758	0.012	230.129
Log of weekday transit frequency	0.647	0.002	297.622	0.684	0.005	133.78
Log of land price	18.786	0.039	481.94	14.983	0.111	134.796
Residual variances						
Log of commerce Kernel density	0.089	0.002	58.770	0.141	0.005	30.836
Log of population density	0.334	0.003	122.394	0.362	0.006	61.793
Log of weekday transit frequency	0.386	0.003	136.627	0.362	0.006	57.246
Log of land price	0.372	0.002	157.392	0.439	0.007	58.670
R^2 (Total explained variance)						
Log of commerce Kernel density	0.911	0.002	604.717	0.859	0.005	187.164
Log of population density	0.666	0.003	243.941	0.638	0.006	109.083
Log of weekday transit frequency	0.614	0.003	217.407	0.638	0.006	101.106
Log of land price	0.628	0.002	265.258	0.561	0.007	75.085
Modification indices	**M.I.**	**E.P.C.**	**Std E.P.C**	**M.I.**	**E.P.C.**	**Std E.P.C**
Log of population density with log of Kernel density	42.262	-0.068	-0.081	9.714	-0.069	-0.068
Log of transit frequency with log of Kernel density	92.063	-0.082	-0.102	19.278	-0.105	-0.095
Log of transit frequency with log of population density	255.343	0.143	0.076	51.76	0.144	0.081
Log of land price with log of Kernel density	255.365	0.036	0.177	51.744	0.048	0.127
Log of land price with log of population density	92.134	-0.022	-0.046	19.23	-0.026	-0.044
Log of land price with log of transit frequency	42.269	-0.014	-0.029	9.714	-0.02	-0.031

E.P.C.: Expected parameter change; STD E.P.C. Fully standardized expected parameter change

CFA sensitivity analysis at different levels of aggregation (Continued)

	600m Hexagon grid			1000m Hexagon grid*		
Sample size	4979			1882		
Chi-Square test						
Value (d.f.)	60.01 (2)			32.949 (2)		
p value	0.000			0.000		
RMSEA (Root Mean Square Error of Approximation)						
Estimate	0.076			0.091		
90% C.I.	(0.060-0.094)			(0.065-0.119)		
Probability RMSEA ≥ .05	0.004			0.005		
CFI/TLI	CFI: 0.994 TLI: 0.982			CFI: 0.991 TLI: 0.974		
SRMR (Standardized Root Mean Square Residual)						
Value	0.014			0.016		
Fully standardized results						
Coefficients	**Estimate**	**S.E.**	**t stat.**	**Estimate**	**S.E.**	**t stat.**
Log of commerce Kernel density	0.931	0.005	181.917	0.931	0.009	107.4
Log of population density	0.690	0.011	64.801	0.693	0.017	41.742
Log of weekday transit frequency	0.791	0.008	98.376	0.774	0.014	55.085
Log of land price	0.736	0.010	73.059	0.739	0.016	44.889
Intercepts						
Log of commerce Kernel density	0.946	0.011	83.277	0.928	0.018	51.143
Log of population density	2.356	0.027	87.716	2.378	0.044	54.067
Log of weekday transit frequency	0.675	0.010	69.035	0.654	0.016	41.882
Log of land price	15.138	0.213	71.025	14.99	0.355	42.285
Residual variances						
Log of commerce Kernel density	0.133	0.010	13.984	0.134	0.016	8.286
Log of population density	0.524	0.015	35.682	0.519	0.023	22.560
Log of weekday transit frequency	0.375	0.013	29.526	0.401	0.022	18.467
Log of land price	0.458	0.015	30.883	0.453	0.024	18.615
R^2 (Total explained variance)						
Log of commerce Kernel density	0.867	0.01	90.959	0.866	0.016	53.700
Log of population density	0.476	0.015	32.401	0.481	0.023	20.871
Log of weekday transit frequency	0.625	0.013	49.188	0.599	0.022	27.542
Log of land price	0.542	0.015	36.53	0.547	0.024	22.445
Modification indices	**M.I.**	**E.P.C.**	**Std E.P.C**	**M.I.**	**E.P.C.**	**Std E.P.C**
Log of population density with log of Kernel density	-	-	-	-	-	-
Log of transit frequency with log of Kernel density	45.264	-0.416	-0.386	22.783	-0.457	-0.418
Log of transit frequency with log of population density	39.880	0.306	0.126	24.549	0.384	0.157
Log of land price with log of Kernel density	39.889	0.103	0.283	24.549	0.135	0.373
Log of land price with log of population density	45.229	-0.099	-0.121	22.784	-0.115	-0.142
Log of land price with log of transit frequency	-	-	-	-	-	-

E.P.C.: Expected parameter change; STD E.P.C. Fully standardized expected parameter change

7.6 MODEL VALIDATION

Although the results presented in Section 7.4 used the full dataset, a fixed-weight partial cross-validation test was conducted to validate the model beforehand. Proposed by MacCallum et al. (1994), the test consists on splitting the dataset into two mutually exclusive random samples. The first sample is used as to calibrate the model, while the second one is used to validate it.

This test differs from the cross-validation test proposed by Browne & Cudeck (1993) in that in instead of fixing all the parameters in the validation models (at the values estimated in the calibration model), only the linear weights are fixed, allowing the variances and covariances to be freely estimated. The theoretical support for this test comes from the assumption that the while the linear effects are assumed equal for all samples, variances and covariances of variables might reflect variations with different sampling groups, which are expected even in ideal cases (MacCallum, et al., 1994). Although the test is also used as a tool for model selection between alternative models, in this particular case the test objective is to validate on an independent sample a model that resulted from an exploratory process of potential indicator variables.

As shown in Table 7-3, both the calibration and the validation models exhibit acceptable goodness of fit indices, with the exception of a significant Chi-square statistic, which as explained earlier is attributed to the large sample size. Based on these results it is suggested that the model is robust to sampling variations, which supports the specification using the full sample size presented earlier.

It is important to note that when implementing the model in other cities, although the same factor structure might apply, it is expected that the size of the factor loadings, variances and covariances, and error covariances behave in a different way as well. It might be plausible that the factor structures differ as well, as each different city might be considered as a different population. However, the model presented in this chapter should serve as a starting point for an exploratory analysis on a different city, subject to validation.

Table 7-3 CFA Model validation against 2 random sample subsets

	Calibration sample			Validation sample		
Sample size	9243			9244		
Chi-Square test						
Value (d.f.)	24.422	(2)		30.722	(5)	
p value	0.000			0.000		
RMSEA (Root Mean Square Error of Approximation)						
Estimate	0.035			0.024		
90% C.I.	(0.023-0.048)			(0.016-0.032)		
Probability RMSEA ≥ .05	0.974			1.000		
CFI/TLI	CFI: 0.998	TLI: 0.995		CFI: 0.999	TLI: 0.999	
SRMR (Standardized Root Mean Square Residual)						
Value	0.005			0.005		
Unstandardized results						
Coefficients	**Estimate**	**S.E.**	**t stat.**	**Estimate**	**S.E.**	**t stat.**
Log of commerce Kernel density	1.000	fixed	fixed	1.000	fixed	fixed
Log of population density	0.864	0.01	89.155	0.864	fixed	fixed
Log of weekday transit frequency	0.949	0.009	101.403	0.949	fixed	fixed
Log of land price	0.271	0.003	86.433	0.271	fixed	fixed
Intercepts						
Log of commerce Kernel density	2.001	0.022	91.879	2.040	0.022	92.170
Log of population density	5.866	0.022	266.507	5.911	0.022	263.925
Log of weekday transit frequency	1.559	0.024	64.988	1.613	0.024	66.455
Log of land price	10.625	0.007	1445.77	10.636	0.007	1435.13
Residual variances						
Log of commerce Kernel density	0.616	0.027	23.162	0.634	0.023	27.288
Log of population density	1.664	0.038	43.691	1.645	0.034	47.793
Log of weekday transit frequency	1.925	0.045	43.072	1.964	0.041	48.220
Log of land price	0.222	0.007	32.075	0.222	0.007	32.120
R^2 (Total explained variance)						
Log of commerce Kernel density	0.859	0.007	132.031	0.860	0.005	160.023
Log of population density	0.629	0.008	73.988	0.639	0.006	108.547
Log of weekday transit frequency	0.638	0.009	70.630	0.642	0.006	104.106
Log of land price	0.556	0.010	53.428	0.566	0.008	69.847
Modification indices	**M.I.**	**E.P.C.**	**Std E.P.C**	**M.I.**	**E.P.C.**	**Std E.P.C**
Log of population density with log of Kernel density	10.956	-0.115	-0.106	-	-	-
Log of transit frequency with log of Kernel density	-	-	-	10.716	-0.086	-0.086
Log of transit frequency with log of population density	23.986	0.141	0.079	25.52	0.127	0.127
Log of land price with log of Kernel density	23.992	0.047	0.126	15.512	0.03	0.030
Log of land price with log of population density	10.951	-0.028	-0.047	4.719	-0.017	-0.017
Log of land price with log of transit frequency	-	-	-	5.686	-0.021	-0.021

E.P.C.: Expected parameter change; STD E.P.C. Fully standardized expected parameter change

7.7 DISCUSSION

This chapter proposed an improved model to estimate the urbanization level construct. The proposed method addresses the MAUP problem by using a regular aggregation scheme to define the spatial unit of analysis. In addition, a sensitivity analysis of scale aggregation suggests that estimated parameters are rather robust to aggregation, although model goodness of fit statistics deteriorate as scale increases. Although whether or not the data aggregation can be pinpointed as the main factor behind this apparent lack of fit remains unanswered, and notwithstanding the existing limitations of current goodness of fit statistics, it seems reasonable to choose more disaggregated models where goodness of fit statistics suggest acceptable fit.

In terms of model validation, results from a fixed-weight partial cross-validation test support the current model specification. That being said, this should not be interpreted as meaning that the estimated parameters can be successfully generalized to other cities. Although the selected indicators are based on urban economics and planning theory, heterogeneity of built environment characteristics among cities might result in different factor loadings, variances, covariances and error covariances, if not a different factor structure altogether. Put another way, each city might be consider an independent population for which a specific model should be estimated. The estimated model, however, should serve as a departing point to conduct an exploratory analysis that should then be validated similarly to the way described in this chapter.

The next chapter will focus on an empirical application of the propensity score function on Fukuoka City using the improved urbanization level index, where the MAUP problem is re-visited focusing on the effects of data aggregation on the built environment parameter estimates.

CHAPTER 8 VALIDATION OF THE PROPENSITY SCORE APPROACH: EMPIRICAL APPLICATION IN FUKUOKA CITY

8.1 INTRODUCTION

Having proposed an improved methodology to estimate the treatment variable, this chapter focuses on the validation of the propensity score approach. A methodological comparison against ordinary least squares is conducted through Monte Carlo simulation assuming both a constant and a variable treatment. After establishing the bias reduction potential of the propensity score approach, the method is tested against survey data from Fukuoka City. The MAUP problem is revisited again by conducting a multi-scale analysis to evaluate the sensitivity of results to changes in in the scale of aggregation of the treatment variable when estimating the propensity score function. Finally additional tests are conducted to evaluate the robustness of both methods to model misspecifications. Findings suggest that the propensity score function is indeed more robust to model misspecifications than OLS.

8.2 FUKUOKA CITY SURVEY DESIGN AND DATA CHARACTERISTICS

The principal data source for this analysis was an online survey conducted in the city of Fukuoka, Japan. The survey was conducted in December 2013, through Macromill, Inc. a net research company with over 2.3 million monitors all over Japan. The survey was pre-tested using a convenience sample of students and faculty in the Department of Urban Engineering of the University of Tokyo.

An effective sample size of 656 adult individuals was gathered through stratified random sampling from the monitor database to match the population distribution of the city in terms of household composition. Table 8-1 compares the population distribution to the sampling distribution. The single elder cohort was underrepresented in the sample by almost 7 percentage points; conversely, the single young cohort was over-represented the same amount.

Table 8-1 Sample household structure distribution

Household type	Frequency	Sample percentage	Population percentage
Single household	314	47.9%	47.7%
Of which: Young (age 20-64)	*302*	*46.0%*	*39.2%*
Of which: Elder (age 65 and over)	*12*	*1.8%*	*8.5%*
Couples only	101	15.4%	15.1%
Of which: Young (age 20-64)	*60*	*9.1%*	*8.7%*
Of which: Elder (age 65 and over)	*41*	*6.3%*	*6.5%*
Nuclear household (including single parent households)	201	30.6%	31.3%
Three generation household & others	40	6.1%	6.0%
Total	**656**	**100%**	**100%**

Population data source: 2010 population census of Japan

Given the complexity of the survey, a computer interface was considered the best medium given the possibility of automatically tailoring the survey to the respondent's answers as the survey progresses. Certainly there are some issues regarding web surveys that might compromise the external validity of results, particularly the issue of coverage error, which stems from the exclusion of (i) people who do not have access to internet and (ii) have enough digital literacy to adequately answer the questionnaire (Couper, 2000). Regarding access to the internet, the Ministry of Internal Affairs and Communications of Japan (MIC) estimated in their Communications Usage Trend Survey a penetration rate of 79.1% for 2011, with a 90% penetration in the 13-49 years old cohort, and lower rates for the 60-64, 65-69, and 70-79 cohorts, with 73%, 60% and 42% diffusion rates respectively (MIC, 2012); Regarding digital literacy, the same survey estimates that among internet users, 60% used the internet for online purchases or trade of merchandise, although it noted a gap between users under 49 years old and users above that threshold. This suggests that although there is a rather high internet diffusion rate, some limitations do exist in terms of representativeness of the sample, especially for the older cohorts.

The survey consisted of 4 main sections, namely, individual and household attributes, mobility biography, attitudes and habits, and travel behavior. The next sub-sections describe the general characteristics of each section. The survey differs from the Hiroshima survey mainly in that it gathers data of respondents' previous residential locations as well as previous travel behavior, which following the discussion in Section 5.5 are hypothesized as factors affecting residential location choice.

8.2.1 Individual and household attributes

General sample characteristics were compared against population characteristics from the 2010 national census and other sources to check the representativeness of the sample (see Table 8-2). Overall the sample mean values approximate the census mean values in the evaluated criteria.

Table 8-2 Individual and household sample characteristics

Variable name	Mean	Population Mean	Std.Dev.
Household attributes		*2010 Census data*	
Household size	2.210	2.010	1.405
Number of workers in household (part-time included)	1.095	-	0.737
Number of drivers (have a valid driver's license)	1.823	-	1.304
Number of small children under 6 years old	0.174	-	0.456
Number of children under 16 years old	0.454	-	0.813
Number of bicycles in household	1.204	-	1.188
Number of vehicles in household	0.698	1.086[1]	0.701
Bicycle owning household (at least one)	0.710	-	0.454
Car owning household (at least one)	0.585	-	0.493
Household yearly income		*NTA National average*	
Under JPY2,000,000	0.200	0.239	0.400
From JPY2,000,001 to JPY3,000,000	0.180	0.171	0.384
From JPY3,000,001 to JPY4,000,000	0.159	0.181	0.366
From JPY4,000,001 to JPY5,000,000	0.120	0.139	0.326
From JPY5,000,001 to JPY6,000,000	0.107	0.094	0.309
From JPY6,000,001 to JPY7,000,000	0.066	0.057	0.248
From JPY7,000,001 to JPY8,000,000	0.064	0.040	0.326
From JPY8,000,001 to JPY9,000,000	0.032	0.025	0.176
From JPY9,000,001 to JPY10,000,000	0.018	0.017	0.134
From JPY10,000,001 to JPY12,000,000	0.034	0.038	0.180
Over JPY12,000,000	0.021		0.145
Individual attributes		*2010 Census data*	
Male	0.479	0.473	0.500
Age	43.433	41.900	13.385
Driver (Valid driver's license)	0.887	0.620	0.317
Worker (as primary occupation)	0.660	-	0.474
Student (as primary occupation)	0.061	-	0.239
Worker (as secondary occupation)	0.081	-	0.273
Student (as secondary occupation)	0.005	-	0.068
Education level			
Middle school or high school diploma	0.276	-	0.447
Technical school	0.235	-	0.424
Bachelor degree	0.433	-	0.496
Graduate degree (Master's or Ph.D.)	0.056	-	0.231

[1] Source: http://www.airia.or.jp/publish/pdf/happyou/2010_08setai.pdf (Prefectural estimate)

Although on average online surveys are expected to be biased towards the young, the average age in the sample is slightly higher than the mean population value, mainly as a result of the exclusion of the under-20-years-old cohort. Sample average household size is also larger, with a sample average of 2.21 against the population average of 2.01. Compared against the Private Income Statistical Survey for 2011 (National Tax Agency, 2012), In general the income distribution is rather similar to the national average distribution, although consistent with the web-survey literature (Couper, 2000), higher income households are slightly over-represented in samples while lower income cohorts are somewhat underrepresented.

In terms of car ownership, the sample mean was estimated at 0.7 vehicles per household against a mean population value of 1.1 per household (compared against prefectural estimates). On the other hand, the ratio of driving license holders stood at 89% against a population ratio of 62%, although this difference might also be partly explained by the exclusion of the under-20-years-old cohort.

8.2.2 Mobility biography

The mobility biography section of the survey follows recommendations Axhausen (2008) in order to gather data on (i) previous residential locations and (ii) main transport mode during previous life stages.

In order to account for the effect of built environment characteristics at previous locations respondents were asked to indicate the address of the 3 places where they have spent most of their lives (besides their current location, which was asked separately). In addition respondents were asked to state the life-course event, if any, motivating the relocation, the time period they spent at each location, the type of housing, layout and number of vehicles owned during that period. On average the survey captured 65% of respondents lifetime share throughout the 4 locations asked. For 30% of the sample the survey accounted for over 90% of respondent's lifetime. Figure 8-1 illustrates the distribution of the lifetime share accounted for.

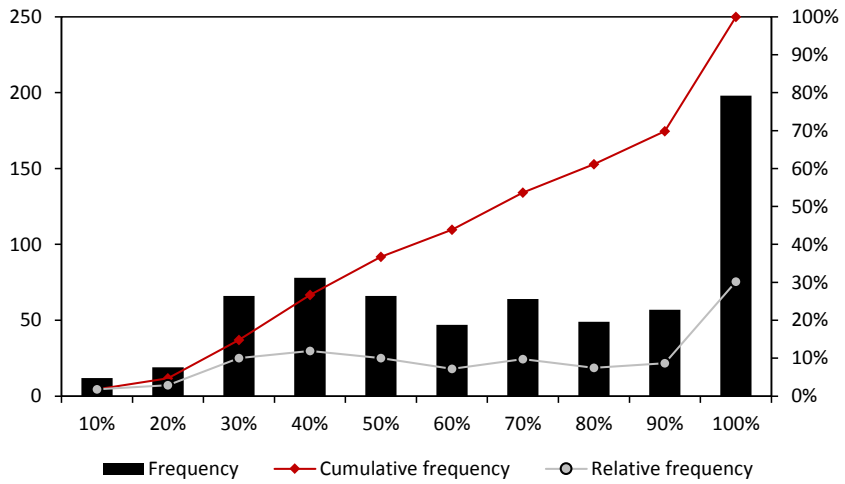


Figure 8-1 Lifetime share accounted for in terms of residential location (present location + 3 past locations)

Regarding life-course events motivating the relocation, as illustrated in Figure 8-2, the three most reported events were employment related events (start, or change of workplace) with 19.3%, school related events with 15.4% and marriage with 9.7%. For 19% of relocations, there was no event in particular motivating the relocation, while 10% of the sample reported they have not moved from the place where they were born.

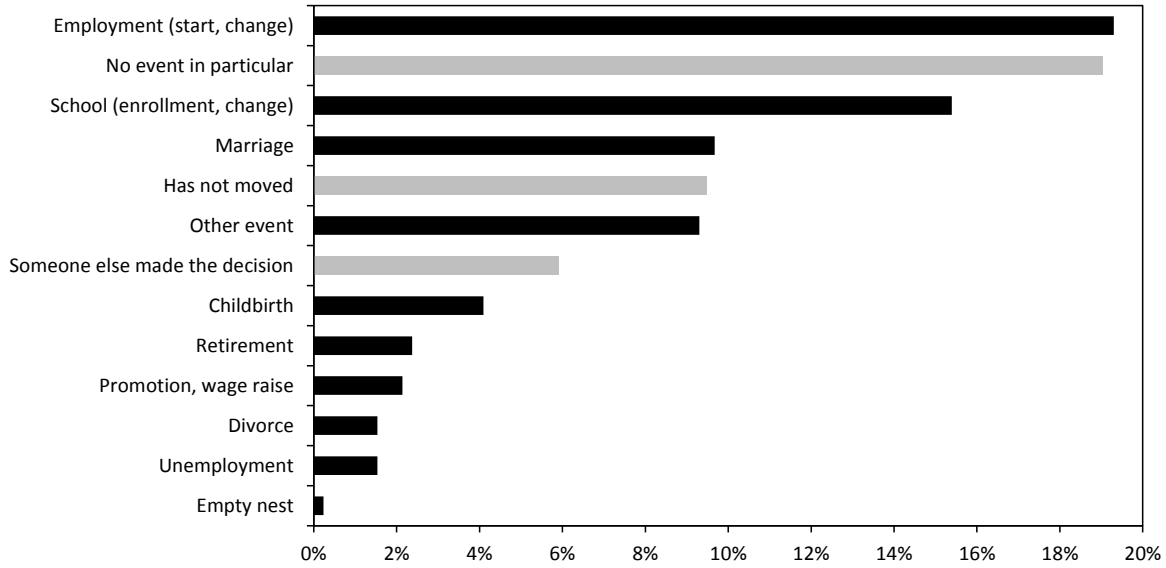


Figure 8-2 Major life-course events motivating residential relocation

The second mobility biography aspect of interest was main mode of transport during past life periods. Respondents were asked to state their main mode of transport from birth until present

separated by time periods. On average, the survey captured 64% of respondents' lifetime. Figure 8-3 illustrates the distribution of the lifetime share accounted for.

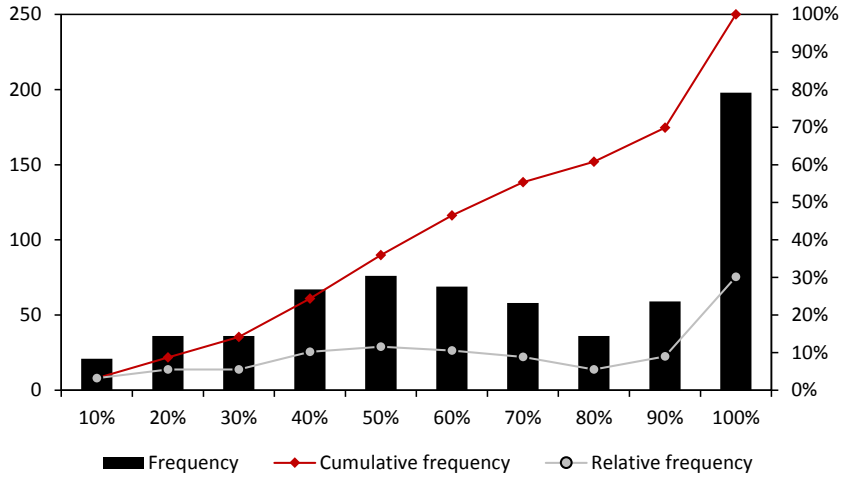


Figure 8-3 Lifetime share accounted for in terms of main modes of transport at previous life periods

Figure 8-4 illustrates the average lifetime share spent using a given mode as main transport mode by age cohort. Overall car (both as driver of passenger) and transit are on average the main modes of transport for almost all age cohorts. This preeminence becomes stronger for higher age-cohorts. Consequently, non-motorized modes, although exhibiting considerably high shares in the 20-29 and 30-39 age cohorts, display at marked trend downwards as age increases.

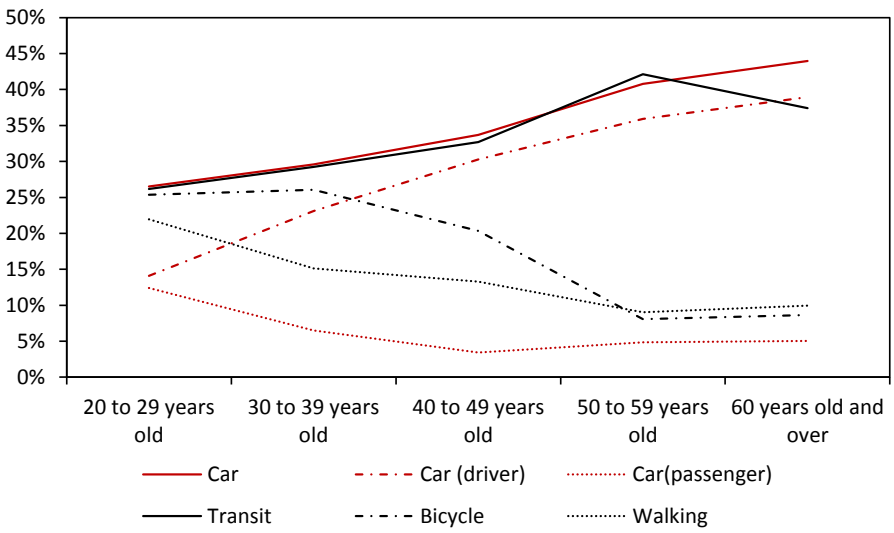


Figure 8-4 Average lifetime share using a given transport mode by age cohort

8.2.3 Attitudes and habits

8.2.3.1 Automobile use habit

Similar to the Hiroshima case, the Response Frequency Index (RFI) proposed by Verplanken et al. (1994) was used to measure habits. Respondents were presented with 10 hypothetical trips and given six travel modes (Car, train, bicycle, walk, motorbike and other) to choose from. Habit was measured as the simple summation of all the times car mode was selected (See Section 6.3.2. for more details on the theoretical regarding the CFI). The car habit mean value was 4.09 with a standard deviation of 3.40. As expected the RFI index was negatively correlated moderately with the estimated urbanization level index (-0.34 $p<0.01$).

8.2.3.2 Attitudes towards residential location and transport

To measure attitudes and preference the same set of items as in the Hiroshima survey were used, where respondents were asked to rate on a five point Likert Scale the level of agreement with 30 statements regarding private vehicles, public transport, non-motorized modes and residential location. Principal component analysis (PCA) was used to estimate the factors that explain unobserved attitudes towards residential location and transport, where the number of factors was decided based on parallel analysis with 500 replications as illustrated in Figure 8-5.

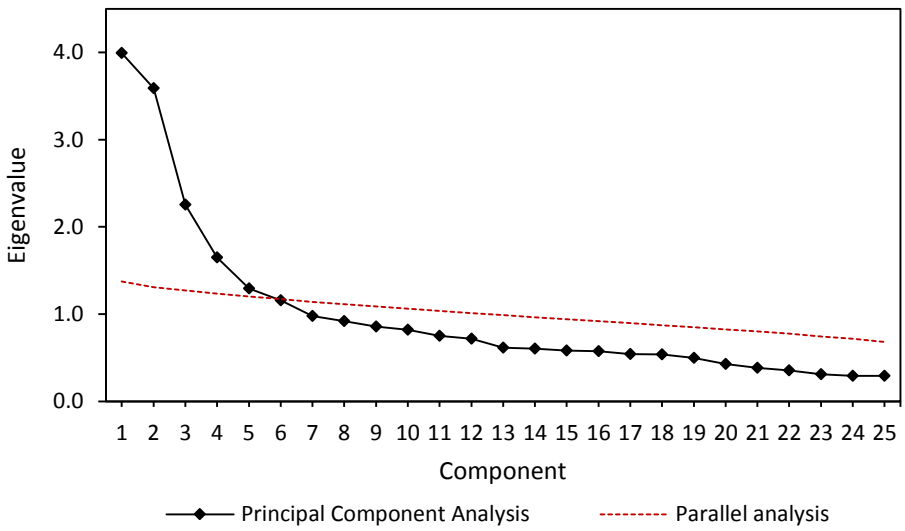


Figure 8-5 Parallel analysis of research data and random data

Although the parallel analysis results suggested a five factor solution a five factor solution was not conceptually sound solution, hence a three factor solution was selected as shown in Table 8-3.

Table 8-3 summarizes the factor loadings for the extracted factors. The number of extracted factors in this solution is, however, different from the Hiroshima solution where four factors were extracted. In the four factor solution for Fukuoka many indicators were cross loading on two factors, which resulted in the merging of the two into a single factor named "Car dependent and suburban preference". For the remaining two factors, the indicators that loaded on each factor were very similar for both the Hiroshima and Fukuoka cases.

Table 8-3 Factor loadings for residential location and transport related attitudes

Factor	Statement	Loading
Car dependent & Suburban preference	I prefer living in a place where it's easy to guarantee a parking space	0.643
	Driving a car gives me a sense of freedom	0.633
	I like driving	0.609
	More roads should be built to improve traffic conditions	0.589
	In general, the car is the safest transport mode	0.579
	I prefer living in a large house over having good transit accessibility	0.569
	Owning a car is a symbol of social status	0.551
	The suburbs are a better places to raise a family than the city center	0.540
	Before giving up driving altogether, I'd switch to an environmentally friendly car	0.465
	As much as possible, I prefer not living in multi-family housing	0.388
	I prefer living in a place close to a large-scale shopping center	0.368
	The cost of riding public transport are higher than the costs of driving a car	0.359
	Buses and trains are unreliable	0.335
Pro-alternative modes	Whenever possible, I prefer riding public transport than driving	0.745
	Whenever possible, I prefer walking or riding a bicycle than driving	0.744
	I like walking	0.630
	I like riding a bicycle	0.538
	Riding the bus or the train is comfortable	0.519
	Gas prices should be raised as a countermeasure to traffic jams and air pollution	0.485
	Using tax money to pay for public transport improvements is a good investment	0.466
Urbanite	I prefer living in a place with good access to the city center	0.789
	Living in a place with good transit accessibility is important	0.770
	If I were to move, I would prefer moving to the city center than to the suburbs	0.705
	Living in walking or biking range of different shops is important	0.691
	I prefer living in a place that is close to different amenities, even if I have to live in a smaller house	0.660
	I prefer living in a large house over having good transit accessibility	-0.372
	As much as possible, I prefer not living in multi-family housing	-0.328

Extraction Method: Principal Component Analysis; Rotation Method: Promax with Kaiser Normalization.
Statements translated from the Japanese. See the appendix for the original questionnaire

This difference in results highlight yet again the limitations of the current methodologies for measuring attitudes and preferences, particularly the lack of an overarching theory guiding these measurements, and the yet exploratory nature of the current efforts.

8.2.4 Travel behavior

The travel behavior variables considered for this analysis were home-based maintenance trips (which excludes discretionary activities). Respondents were asked to state the number of trips (excluding the return trip) taken during the week before up to the survey day by purpose and mode (see Table 8-4).

Table 8-4 Summary of reported travel behavior characteristics of the sample

Variable name	Mean	Std. Dev.	Minimum	Maximum
Total home-based maintenance trips	4.358	3.616	0	50
Of which: Car trip	*1.321*	*1.955*	*0*	*11*
Of which: Transit trips	*0.295*	*0.894*	*0*	*10*
Of which: Non-motorized trips	*2.741*	*3.301*	*0*	*40*

8.3 MOTIVATING THE ANALYSIS: ORDINARY LEAST SQUARE ESTIMATION OF TRIP FREQUENCY BY MODE

In order to motivate the analysis, consider the ordinary least square estimates of maintenance trips by mode of the general form:

$$(40) \qquad f_{im}(T^A) = \alpha + T^A\beta + \boldsymbol{X_i\delta} + \varepsilon$$

where $f_i(T^A)$ is the log observed trip frequency for individual i in mode m. T^A is the treatment of interest, that is, urbanization level at home location, and $\mathbf{X_i}$ is a vector of covariates associated with the observed outcomes and/or the treatment T^A as hypothesized in Figure 5-2. For now, the multi-scale issue is not considered and the treatment is considered only at the original estimation scale (300 meter diameter hexagons). For each mode m, three nested models are estimated. A socio-demographics only model (Model A), a built-environment model (Model B), and a full model (Model

C) which includes the full set of covariates including attitudes and habits. Estimation results for car, non-motorized and transit trips are summarized in Table 8-5, Table 8-6, and Table 8-7 respectively.

Regarding car trips, the models perform rather well with R^2 values of 0.27, 0.34, and 0.47 for models A, B and C, respectively. As expected, urbanization level at home location is statistically significant and negatively associated with car trip frequency. Consistent with the stated hypotheses, individual attitudes and habits were also statistically significant.

Table 8-5 OLS estimates of home-based maintenance trips by car

	Model A: Socio-demographics			Model B: Model A + built environment			Model C: Model B + attitudes and habits		
N	491			491			491		
Parameters	12			13			17		
d.f.	479			478			474		
RSS	167.43			154.46			123.48		
S.E. of e	0.59			0.57			0.51		
R-square	0.29			0.34			0.47		
Adj. R-square	0.27			0.32			0.46		
F test (p-value)	17.46 (.0000)			20.65 (.0000)			26.65 (.0000)		
Variable	β	**S.E.**	**t-Stat**	β	**S.E.**	**t-Stat**	β	**S.E.**	**t-Stat**
Constant	0.010	0.185	0.055	**0.569**	**0.201**	**2.839**	**0.581**	**0.1955**	**2.973**
Socio-demographics									
Age	**0.004**	**0.002**	**1.906**	**0.004**	**0.002**	**1.868**	**0.005**	**0.002**	**2.501**
Male	0.040	0.060	0.665	0.007	0.058	0.120	-0.015	0.053	-0.282
Driver	0.081	0.080	1.015	0.127	0.079	1.600	0.010	0.077	0.130
Worker	-0.049	0.062	-0.788	-0.027	0.060	-0.446	**-0.101**	**0.057**	**-1.771**
Nuclear HH	0.055	0.150	0.370	0.068	0.155	0.441	-0.070	0.145	-0.484
Couple HH	0.045	0.167	0.269	0.065	0.171	0.383	-0.055	0.155	-0.356
Single HH	-0.008	0.155	-0.050	0.048	0.159	0.300	0.025	0.148	0.166
No. of cars	**0.504**	**0.054**	**9.357**	**0.417**	**0.055**	**7.599**	**0.117**	**0.062**	**1.885**
No. of bikes	**-0.054**	**0.028**	**-1.972**	**-0.057**	**0.026**	**-2.181**	-0.032	0.024	-1.341
Mid income[1]	0.062	0.069	0.892	0.078	0.066	1.192	0.087	0.056	1.547
High income[2]	-0.036	0.088	-0.406	0.026	0.084	0.313	0.043	0.072	0.591
Built environment									
Urbanization level (S1)	-	-	-	**-0.296**	**0.044**	**-6.693**	**-0.211**	**0.041**	**-5.119**
Attitudes and habits									
Car habit	-	-	-	-	-	-	**0.085**	**0.011**	**7.400**
Lifetime ratio using transit	-	-	-	-	-	-	**-0.241**	**0.081**	**-2.969**
Lifetime ratio using NMM	-	-	-	-	-	-	**-0.211**	**0.079**	**-2.659**
Pro-alternative modes	-	-	-	-	-	-	**-0.060**	**0.027**	**-2.201**

[1] JPY 5 million – 8 million; [2] over JPY 8 million

Table 8-6 OLS estimates of home-based maintenance trips by non-motorized modes (NMM)

	Model A: Socio-demographics			Model B: Model A + built environment			Model C: Model B + attitudes and habits		
N	491			491			491		
Parameters	12			13			18		
d.f.	479			478			473		
RSS	252.22			241.64			211.22		
S.E. of e	0.73			0.71			0.67		
R-square	0.15			0.19			0.29		
Adj. R-square	0.13			0.17			0.25		
F test (p-value)	7.82 (.0000)			9.21 (.0000)			26.65 (.0000)		
Variable	β	**S.E.**	**t-Stat**	β	**S.E.**	**t-Stat**	β	**S.E.**	**t-Stat**
Constant	**1.007**	**0.231**	**4.368**	**0.502**	**0.249**	**2.014**	**0.419**	**0.249**	**1.683**
Socio-demographics									
Age	0.004	0.003	1.435	0.004	0.003	1.560	**0.005**	**0.003**	**1.857**
Male	**-0.157**	**0.073**	**-2.139**	**-0.127**	**0.073**	**-1.749**	-0.102	0.068	-1.504
Driver	0.029	0.110	0.262	-0.012	0.107	-0.115	0.103	0.101	1.024
Worker	**-0.249**	**0.074**	**-3.350**	**-0.269**	**0.073**	**-3.672**	**-0.171**	**0.069**	**-2.481**
Nuclear HH	0.125	0.162	0.769	0.113	0.165	0.683	0.227	0.151	1.501
Couple HH	0.157	0.180	0.870	0.138	0.182	0.760	0.227	0.160	1.414
Single HH	0.272	0.178	1.533	0.222	0.182	1.225	0.208	0.162	1.284
No. of cars	**-0.382**	**0.058**	**-6.546**	**-0.303**	**0.062**	**-4.886**	-0.040	0.063	-0.648
No. of bikes	**0.097**	**0.029**	**3.314**	**0.099**	**0.029**	**3.426**	**0.062**	**0.027**	**2.285**
Mid income[1]	0.003	0.080	0.033	-0.012	0.079	-0.153	-0.027	0.071	-0.377
High income[2]	-0.018	0.097	-0.187	-0.074	0.096	-0.769	-0.081	0.088	-0.913
Built environment									
Urbanization level (S1)	-	-	-	**0.267**	**0.057**	**4.711**	**0.174**	**0.053**	**3.299**
Attitudes and habits									
Car habit	-	-	-	-	-	-	**-0.069**	**0.012**	**-5.646**
Lifetime ratio using transit	-	-	-	-	-	-	0.155	0.114	1.364
Lifetime ratio using NMM	-	-	-	-	-	-	**0.313**	**0.110**	**2.856**
Pro-alternative modes	-	-	-	-	-	-	**0.096**	**0.029**	**3.280**
Urbanite attitude	-	-	-	-	-	-	**0.060**	**0.030**	**2.027**

[1] JPY 5 million – 8 million; [2] over JPY 8 million

Car use habit, as measured by the response frequency method (Verplanken, et al., 1994) was positively associated with car trips, while the lifetime ratios using transit and non-motorized modes as main travel modes were negatively associated with car trips, as was the attitudinal factor "Urbanite". As expected, the inclusion of attitudes and habits also reduced the magnitude of the

estimated marginal effect of urbanization level by 28% suggesting that failure to account for these factors might over-estimate the effect of built environment on car trip frequency.

Table 8-7 OLS estimates of home-based maintenance trips by transit

	Model A: Socio-demographics			Model B: Model A + built environment			Model C: Model B + attitudes and habits		
N	491			491			491		
Parameters	12			14			16		
d.f.	479			477			475		
RSS	70.68			69.87			67.08		
S.E. of e	0.38			0.38			0.38		
R-square	0.04			0.05			0.09		
Adj. R-square	0.02			0.03			0.06		
F test (p-value)	1.88 (.0395)			2.03 (.0172)			3.14 (.0001)		
Variable	β	**S.E.**	**t-Stat**	β	**S.E.**	**t-Stat**	β	**S.E.**	**t-Stat**
Constant	0.081	0.124	0.649	0.117	0.141	0.830	0.140	0.132	1.053
Socio-demographics									
Age	**0.004**	**0.002**	**2.346**	**0.004**	**0.002**	**2.569**	**0.003**	**0.001**	**1.944**
Male	-0.031	0.037	-0.837	-0.032	0.037	-0.872	-0.022	0.036	-0.599
Driver	0.053	0.063	0.841	0.051	0.063	0.809	0.088	0.063	1.402
Worker	-0.059	0.040	-1.460	-0.056	0.040	-1.404	-0.055	0.039	-1.414
Nuclear HH	-0.077	0.084	-0.921	-0.071	0.079	-0.900	-0.031	0.072	-0.436
Couple HH	-0.048	0.094	-0.505	-0.048	0.090	-0.534	-0.011	0.082	-0.129
Single HH	-0.024	0.091	-0.268	-0.025	0.087	-0.288	-0.004	0.078	-0.050
No. of cars	**-0.068**	**0.033**	**-2.074**	**-0.075**	**0.035**	**-2.159**	0.005	0.034	0.142
No. of bikes	0.000	0.018	-0.023	0.000	0.018	0.013	0.001	0.017	0.046
Mid income[1]	**0.092**	**0.045**	**2.061**	**0.094**	**0.044**	**2.127**	**0.091**	**0.043**	**2.132**
High income[2]	-0.066	0.042	-1.567	-0.068	0.042	-1.603	**-0.081**	**0.043**	**-1.881**
Built environment									
Log of transit frequency				**0.025**	**0.007**	**3.341**	**0.021**	**0.007**	**2.920**
Log of comm. kernel density	-	-	-	**-0.031**	**0.016**	**-1.967**	**-0.036**	**0.016**	**-2.250**
Attitudes and habits									
Car habit	-	-	-	-	-	-	**-0.023**	**0.006**	**-4.115**
Lifetime ratio using transit	-	-	-	-	-	-	**0.131**	**0.058**	**2.246**

[1] JPY 5 million – 8 million; [2] over JPY 8 million

Regarding NMM, as hypothesized, the urbanization level was positively associated with trip frequency, and similar to the car model, the inclusion of the attitudes and habits reduces the magnitude of the estimated effect, in this case by approximately 36%. The worst performing model was the transit trip frequency one, with R^2 values of 0.04, 0.05 and 0.09 for Models A, B, and C

respectively. A possible explanation for the low performance of these models is the fact that, as opposed to commuting trips, for maintenance trips transit was the least preferred option averaging 0.29 trips per week.

The urbanization level variable was not statistically different from zero, hence different built environment variables were introduced, namely, the log of weekday transit frequency and the log of commercial kernel density (as defined in Section 7.3.1). Weekday transit frequency was positively associated with transit frequency, while on the other hand, commercial Kernel density was negatively associated with transit frequency, suggesting that given higher opportunities around home location, individuals are more likely to travel nearby to meet these needs, likely by non-motorized means.

The inclusion of attitude and habits resulted in a reduction of the magnitude of the transit frequency effect, but an increase in the magnitude of the marginal effect of commercial kernel density. In addition, although car use habit and lifetime ratio using transit were significant, no attitudinal factor was statistically different from zero.

Having estimated OLS treatment effects, recall from Section 5.2 that these models do in fact retrieve unbiased and consistent estimates should the conditional independence assumption (CIA) hold, and in fact the effect in question approaches linearity. However, as the true data generating process is unknown, it is virtually impossible to ascertain that the CIA holds. The next subsection applies a propensity score approach using a continuous treatment variable to reduce estimation bias in the urbanization level effect estimates, validating results through Monte Carlo simulation.

8.4 METHODOLOGICAL COMPARISON THROUGH SIMULATION

The performance of the propensity score methodology described earlier is tested against OLS through Monte Carlo simulation. Two set of simulations are estimated, corresponding to home-based subsistence trips by car and by non-motorized means. Following Rubin & Thomas (2000) and Imai and van Dyk (2004), exponential functions were used to specify two data generating processes (DGP), an

additive model and a multiplicative model, with different levels of linearity. For the additive models, departing from Imai and van Dyk the data generating process is of the form

$$(41) \qquad \mathrm{Y_i} = \delta_i \, T_i^A + \mathrm{c}_1(\lambda) \sum_{k=1}^{K} \boldsymbol{\lambda}_k e^{m_k \boldsymbol{X}_{ik}}$$

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

$$(42) \qquad \mathrm{Y_i} = \delta_i \, T_i^A + \mathrm{c}_2(\lambda) e^{\sum_{k=1}^{K} \lambda_k \boldsymbol{X}_{ik}}$$

where for the *i*th individual, Y_i is the simulated outcome (e.g. home-based maintenance trip frequencies by mode), δ_i is the treatment effect, T_i^A is the assigned treatment, and $\boldsymbol{\lambda}_k$ is a vector of zero-mean Gaussian distributed coefficients for a vector of covariates $\mathbf{X}_i$ of *k* dimensions. The variance of $\boldsymbol{\lambda}_k$ is then used to control the level of linearity of each model. The component *m* in the additive model is a set of independently distributed variables that take values of -1 or +1 with equal probability. Each simulation was run with 1000 replications. In these applications the constants $\mathrm{c}_1(\lambda)$ and $\mathrm{c}_2(\lambda)$ are fixed to 1.

The degree of linearity of each model is measured by the average R^2 value of the regression of each function on the set of covariates **X** based on a 1000 replications[12]. For each DGP three levels of linearity are considered. A highly linear model with average $R^2 \approx .95$, a moderately linear model with average $R^2 \approx .85$, and a moderately non-linear model average $R^2 \approx .75$.

As in Rosenbaum & Rubin (1984) and Imai & van Dyk (2004), the simulations are conducted under the assumption that the true propensity score function in known.

8.4.1 Estimating the propensity score function

As explained in Section 5.4, an estimate of the propensity score function $\hat{\theta}$ for the continuous treatment variable urbanization level is estimated through an OLS regression. Covariate selection was based both on findings from the literature as well as the theoretical considerations discussed in

[12] Covariates are fixed among all replications as the observed values in the dataset are used.

Chapter 3. Three types of variables are included in the regression function: household characteristics, lifetime events motivating the relocation and individual characteristics such as education level, habits and attitudes, which are assumed representative of those members involved in the residential location choice decision. Estimation results are presented in Table 8-8. R-squared of the final model was 0.25 suggesting an acceptable model fit.[13]

Table 8-8 Propensity Score OLS Estimation Results

N	491	S.E. of e	0.5331	
Parameters	19	R-square	0.25	
d.f.	472	Adj. R-square	0.22	
RSS	134.14	F test (p-value)	8.66 (.0000)	
Variable		β	**S.E.**	**t-Stat**
Constant		1.505	0.337	4.467
Household characteristics				
Household size		-0.087	0.039	-2.219
Number of children		0.110	0.053	2.079
Number of cars		-0.164	0.060	-2.726
Driver to car ratio		0.249	0.100	2.477
Number of workers		0.049	0.037	1.339
High Income		0.141	0.066	2.144
House is company/school lodge		-0.193	0.132	-1.465
Job located in city center		0.072	0.048	1.487
Lifetime events motivating relocation				
School(Start, change)		0.132	0.080	1.648
Wedding		-0.156	0.079	-1.981
Empty nest		0.707	0.327	2.161
Job promotion		-0.201	0.149	-1.354
Individual characteristics				
University degree holder		0.060	0.047	1.258
Attitudes and habits				
Attitude: Car lover		-0.035	0.025	-1.392
Attitude: Urbanite		0.059	0.025	2.368
Car use Habit		-0.034	0.012	-2.796
Life ratio using transit		0.103	0.068	1.503
Log of weighted population density at previous locations		0.049	0.033	1.517

It is important to note that as a prediction model, the object of interest of this regression is not the individual coefficients of each explanatory variable, but the scalar estimate $\hat{\theta}$. Following the

[13] The propensity score function is the same for both the simulation and the empirical analysis.

balancing score assumption described in equation (24), $\hat{\theta}$ balances all the covariates thought to affect treatment allocation. This warrants the inclusion in the final model of variables that although theoretically significant might be rendered insignificant or exhibit the wrong sign due to multicollinearity.

To verify the balancedness of covariates given $\hat{\theta}$, as suggested by Imai and Van Dyk (2004) each covariate was regressed against the original treatment variable. The same regressions were then run a second time but this time conditioning on $\hat{\theta}$. OLS was used for continuous covariates while binary logit was used for dummy covariates. As Figure 8-6 illustrates, without controlling for $\hat{\theta}$, most covariates are strongly correlated with the treatment, but once conditioned on the propensity score estimate, this correlation is considerably reduced, evident in the drop of the t-statistics for each covariate.

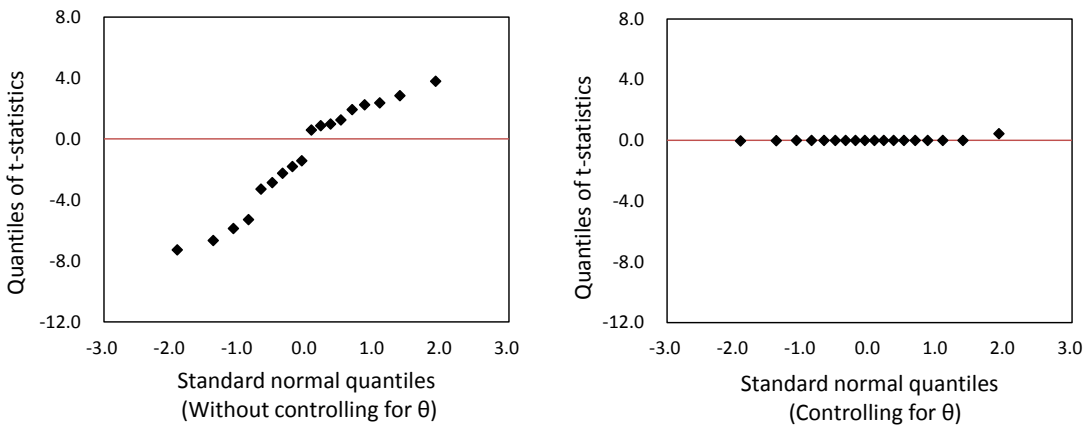


Figure 8-6 Standard Normal Quantile Plots of t-Statistics of covariates with and without controlling for the propensity score estimate

8.4.2 Measuring the performance of the propensity score stratification against OLS

For each of the 12 model specifications (3 additive models x 3 multiplicative models x 2 outcome variables), treatment effect is estimated using OLS, and propensity score stratification stratified on $\hat{\theta}$ into roughly equal sub-classes *j,* where *j*= 3, 5 and 7 strata respectively. In addition all models are estimated with no covariates, and with the full set of covariates, totaling 72 models.

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

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

and mean squared error where

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

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

In terms of treatment effects, performance comparison is conducted first under the assumption of a fixed treatment effect that is constant to all individuals, and second, under the assumption of a variable treatment effect defined as a function of another variable. For the constant treatment effect, the estimated OLS values from the full models presented in Section 8.3 are used. In the variable treatment case the treatment parameter was defined as a function of car use habit, where for individual *i*

(45) $$\tilde{\delta}_{\mathrm{i}} = 10^{-1}(10 - \mathrm{H})\ \delta_m$$

where H is the car use habit index as measured by the Response Frequency Index method, and δ_m is equivalent to the constant treatment parameter for mode m. Under this function, the treatment effect tends to zero as the car use habit increases. This is, however, an arbitrary function in order to illustrate the variable treatment case, but another function might have been used as well.

For the constant treatment case, simulated results are shown in Table 8-9 and Table 8-10 for car trips and NMM trips respectively, while Table 8-11 and Table 8-12 illustrate results for the variable treatment case. Results are given in percentage bias change (or MSE change) relative to the OLS estimates. Positive values indicate that the model underperforms the benchmark OLS model (bias increases relative to OLS), while negative values suggest that the model outperforms the benchmark model (bias decreases relative to OLS).

Table 8-9 Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by car (Constant treatment)

	3 strata		5 strata		7 strata	
% Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	7.43%	-1.90%	-1.89%	**-52.34%**	-15.24%	-26.89%
Moderately linear	9.94%	-2.82%	0.42%	**-51.25%**	-13.63%	-27.67%
Moderately non-linear	6.08%	-2.12%	-3.12%	**-52.90%**	-16.03%	-27.09%
Multiplicative models						
Highly linear	90.73%	-20.54%	22.33%	**-41.93%**	2.09%	-34.58%
Moderately linear	54.19%	-11.06%	5.59%	**-40.21%**	-4.28%	-12.54%
Moderately non-linear	17.14%	-17.68%	6.65%	**-28.08%**	2.28%	-10.91%
%Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	36.36%	-5.17%	13.61%	**-73.88%**	-20.05%	-47.31%
Moderately linear	44.43%	-7.51%	20.41%	**-72.30%**	-15.76%	-48.76%
Moderately non-linear	33.26%	-5.13%	11.06%	**-74.36%**	-21.19%	-47.31%
Multiplicative models						
Highly linear	384.55%	-41.61%	131.18%	**-70.69%**	41.03%	-49.44%
Moderately linear	137.92%	-45.90%	9.11%	**-82.97%**	-4.41%	-45.50%
Moderately non-linear	19.32%	-49.49%	2.47%	**-62.45%**	-4.59%	-51.94%

N.C.: No covariates; A.C.: All Covariates

Table 8-10 Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by NMM (Constant treatment)

	3 strata		5 strata		7 strata	
% Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	91.45%	-20.17%	13.69%	**-45.48%**	-10.20%	-44.82%
Moderately linear	42.77%	-16.80%	3.80%	-31.81%	-7.11%	**-32.77%**
Moderately non-linear	41.74%	-3.95%	13.14%	**-26.27%**	4.21%	1.93%
Multiplicative models						
Highly linear	5.54%	-1.76%	-3.63%	**-53.11%**	-16.29%	-26.78%
Moderately linear	2.65%	-1.46%	-6.26%	**-54.25%**	-17.87%	-26.56%
Moderately non-linear	9.66%	-2.54%	0.13%	**-51.49%**	-13.93%	-27.41%
% Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	173.19%	-34.20%	23.96%	**-73.37%**	-23.26%	-70.55%
Moderately linear	69.67%	-42.41%	4.01%	**-72.85%**	-13.35%	-68.13%
Moderately non-linear	61.30%	-22.94%	12.58%	**-60.43%**	1.35%	-33.21%
Multiplicative models						
Highly linear	36.44%	-5.62%	13.71%	**-73.80%**	-19.76%	-47.59%
Moderately linear	28.86%	-4.73%	7.41%	**-75.11%**	-23.02%	-47.08%
Moderately non-linear	40.15%	-6.19%	16.79%	**-73.16%**	-18.09%	-47.94%

N.C.: No covariates; A.C.: All Covariates

Table 8-11 Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by car (Variable treatment)

	3 strata		5 strata		7 strata	
Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	71.56%	17.37%	-22.48%	-11.00%	**-76.12%**	-47.57%
Moderately linear	43.31%	5.39%	-5.28%	-30.05%	-34.15%	**-35.12%**
Moderately non-linear	13.46%	-0.57%	-3.98%	**-48.47%**	-19.91%	-28.47%
Multiplicative models						
Highly linear	83.80%	4.16%	-10.38%	-27.72%	-49.54%	**-50.47%**
Moderately linear	52.12%	-15.31%	-0.26%	**-42.93%**	-10.83%	-30.01%
Moderately non-linear	24.86%	-15.01%	7.74%	**-28.15%**	1.67%	-16.06%
Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	193.78%	37.61%	-39.72%	-20.98%	**-94.03%**	-72.42%
Moderately linear	87.20%	6.09%	1.98%	**-57.34%**	-38.92%	-55.69%
Moderately non-linear	36.40%	-4.15%	9.90%	**-73.25%**	-22.50%	-47.78%
Multiplicative models						
Highly linear	385.66%	-1.44%	6.43%	-51.12%	-61.59%	**-74.62%**
Moderately linear	128.22%	-40.64%	1.95%	**-83.00%**	-17.77%	-65.17%
Moderately non-linear	27.17%	-45.21%	1.31%	**-62.79%**	-9.19%	-57.75%

N.C.: No covariates; A.C.: All Covariates

Table 8-12 Simulated changes in absolute bias and mean squared error compared against the OLS estimates for home-based maintenance trips by NMM (Variable treatment)

	3 strata		5 strata		7 strata	
Change in absolute bias	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	71.74%	17.39%	-22.46%	-10.90%	**-76.19%**	-47.61%
Moderately linear	40.45%	4.83%	-6.05%	-31.68%	-32.52%	**-33.98%**
Moderately non-linear	12.27%	-1.04%	-3.37%	**-49.34%**	-18.75%	-28.26%
Multiplicative models						
Highly linear	121.29%	-15.90%	16.92%	-33.12%	-2.26%	**-45.30%**
Moderately linear	49.74%	-24.81%	12.46%	**-43.38%**	-0.72%	-39.99%
Moderately non-linear	55.90%	-22.06%	28.87%	**-32.75%**	17.65%	-17.53%
Change in mean squared error	**N.C.**	**A.C.**	**N.C.**	**A.C.**	**N.C.**	**A.C.**
Additive models						
Highly linear	194.43%	37.67%	-39.70%	-20.80%	**-94.08%**	-72.48%
Moderately linear	80.91%	6.03%	-0.14%	**-59.00%**	-39.30%	-54.36%
Moderately non-linear	39.71%	-4.94%	13.05%	**-72.74%**	-20.79%	-48.04%
Multiplicative models						
Highly linear	210.75%	-40.19%	16.72%	-71.60%	-24.21%	**-74.01%**
Moderately linear	152.05%	-41.89%	45.23%	**-72.62%**	18.82%	-61.61%
Moderately non-linear	209.94%	-40.94%	100.00%	**-64.68%**	80.73%	-14.71%

N.C.: No covariates; A.C.: All Covariates

Compared to the OLS estimates, models stratified on the propensity score function reduced absolute bias up to 76% and mean squared error up to 94%, with full-covariates 5-strata and 7-strata models performing the best. Although in a very few cases the no-covariates stratified models outperformed all other models, more than 50% of these models underperformed the benchmark models, which supports the inclusion of all covariates in the estimation, a point that has also been noted by Imai and van Dyk (2004).

In general, the simulation results suggest that propensity score stratification is indeed successful in reducing estimation bias against the OLS.

8.5 EMPIRICAL APPLICATION TO HOME-BASED MAINTENANCE TRIPS

Having demonstrated the bias reduction potential of the propensity score approach, the method is applied to the Fukuoka dataset. In addition, a multi-scale analysis is conducted, largely motivated by the modifiable areal unit problem discussed before. Although given the way the treatment variable was estimated, both the zoning and scale problems are to some extent controlled for [14], the actual spatial scale that households consider when evaluating residential location alternatives is in practice not known. Guo & Bhat (2007) addressed this issue in terms of residential location choice models by operationalizing several definitions of "neighborhoods". In addition to the census tracts, Guo & Bhat analyzed radial neighborhoods and network band models given different radii, namely, 0.4 km, 1.6 km and 3.2 km from each residential location alternative. Since the improvement of the more complex network band neighborhood was rather marginal, for this study the simpler radial network operationalization is used.

As illustrated in Figure 8-7 the first scale of analysis (Scale 1) is the same scale at which the urbanization level index was estimated in Chapter 7, that is, a 300m diameter hexagon. The second and third scales take the unweighted average of the urbanization level of all units within a 1500 meter

[14] Recall that data for all indicators except population density is available at the point level and a sensitivity analysis was conducted to evaluate estimate sensitivity to the scale of analysis.

and 3000 meter radii respectively. In addition to the radial neighborhood operationalization, a more conceptually appealing analysis scale is proposed. The fourth scale of analysis assigns a weight to surroundings areas as a function of distance from each unit centroid via a kernel density function as described in Section 7.3.1, so that closer locations are given more importance than more distant ones. Recall that the kernel density function is rather insensitive to bandwidth (radius) specification, making the radius specification irrelevant.

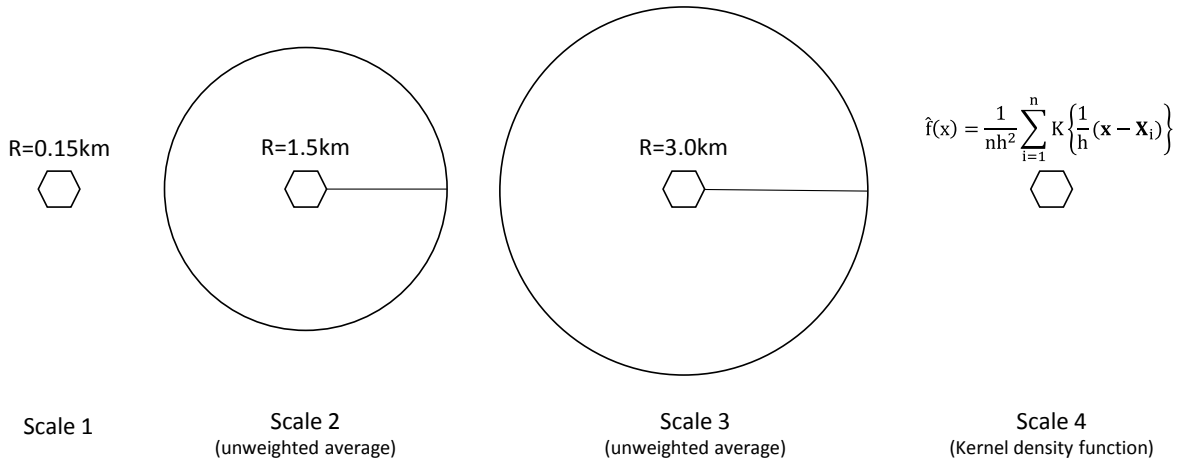


Figure 8-7 Diagram of scale definitions for multi-scale analysis

Table 8-13 and Table 8-14 summarize the treatment effect estimates for OLS against 5-strata and 7-strata models at each spatial scale respectively. For all models, at any scale the direction of the effects is as hypothesized, negative for car trips and positive for non-motorized modes, thus supporting the idea of a mode substitution mechanism between car and non-motorized trips given changes in urbanization level.

Table 8-13 Multi-scale analysis of urbanization effect on home-based maintenance trips against 5 Strata estimates (Full-covariate models)

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

Table 8-14 Multi-scale analysis of urbanization effect on home-based maintenance trips against 7 Strata estimates (Full-covariate models)

		Scale 1		Scale 2		Scale 3		Scale 4	
Model		**OLS**	**7 Strata**	**OLS**	**7 Strata**	**OLS**	**7 Strata**	**OLS**	**7 Strata**
Car trip frequency model	β	-0.201	-0.196	-0.145	-0.223	-0.127	-0.205	-0.131	-0.217
	t-Stat	-4.794	-4.326	-3.191	-4.592	-2.477	-4.220	-3.273	-4.381
	% Δ		-2.4%		54.1%		61.0%		65.8%
NMM trip frequency model	β	0.151	0.160	0.125	0.181	0.089	0.172	0.103	0.187
	t-Stat	2.595	2.545	1.924	2.989	1.215	3.023	1.746	3.245
	% Δ		5.9%		45.3%		92.4%		81.7%

At Scale 1, OLS and propensity score treatment effect estimates are rather similar, with differences ranging from 0.4% to 6% However, at different spatial scales, while the propensity score estimates are rather robust, the OLS estimates deteriorate quickly with difference in estimates up to 101%. Furthermore, in the NMM case, the t-statistics for the OLS estimates fall below the 5% threshold for all but the Scale 1 estimates, becoming insignificant at any significance level for the Scale 3 estimates. The multi-scale issue is certainly a non-trivial issue when considering the neighborhood operationalization problem discussed above. In that sense, the presented results support the use of a propensity score stratification approach over the traditional OLS approach to estimate trip frequencies.

8.6 DISCUSSION OF FINDINGS

This chapter validated through Monte Carlo simulation the propensity score approach as a tool to examine the connection between the built environment and travel behavior from a cross-sectional approach. It is shown that under the ignorability of treatment assumption, the causal effect of urbanization level on travel behavior can be estimated. By testing performance given different data generating processes, simulation results suggest that the propensity score approach can reduce absolute bias up to 76% and mean squared error up to 94% compared to OLS estimates. Empirically, the 5-strata and 7-strata full-covariate models performed the best.

As discussed in Chapter 6, a continuous urbanization level treatment, as the one used here allows for a more precise understanding of the built environment effect on travel behavior at all levels of the urbanization spectrum without the need to arbitrarily draw a defining line between “urban”

and “suburban” which binary treatment models might be highly sensitive to. Empirical analysis of data also suggested that the propensity score approach is more robust to changes in the scale of analysis, whereas the OLS performed rather poorly.

In terms of the propensity score function, the importance of the strong ignorability of treatment assumption cannot be over-emphasized. That is, the assumption that the distribution of treatment outcomes are independent from the distribution of treatment assignment given the propensity score is crucial to the unbiasedness of estimates. Nevertheless, in practice it is impossible to know how well the estimated function approximates the true population function. Although in order to estimate the propensity score function, relevant variables largely cited in the literature introduced in the model, it is assumed at the estimated function is a good estimate of the true unknown function. However, the risk of misspecification is certainly non-trivial. In that sense, much care should be place in estimating the propensity score function, as much of the validity of the analysis depends on it.

CHAPTER 9 CONCLUSION

Motivated by a paradigm change in the conception of what constitutes good urban development, this dissertation sought to validate the existence of a causal mechanism between the built environment and travel behavior. To do so, data from several Japanese cities was analyzed both from a longitudinal and a cross-sectional approach. In general, conditional on several assumptions, findings suggest the existence of a causal mechanism between some dimensions of the built environment and travel behavior. This chapter will summarize the main findings of this dissertation against the existing body of literature on the subject, highlighting the methodological contributions of this work as well as relevant policy implications, and conclude with a discussion of the study limitations and possible future research directions.

9.1 FINDINGS AND CONTRIBUTIONS OF THIS DISSERTATION

Departing from the original research questions stated in Section 1.2, empirically, the main contribution of this dissertation is the validation of the existence of a causal effect between the some dimensions of the built environment and travel behavior. Methodologically, the main contribution is the implementation and validation of a methodology to estimate causality from cross sectional data. In that sense, findings and contributions can be summarized as:

1. Estimation of a causal mechanism between changes in built environment characteristics and changes in trip frequencies by mode using panel data.

2. Operationalization of a continuous index to measure built environment characteristics.

3. Implementation and validation of a methodology to assess the causality problem from a cross-sectional approach.

4. Estimation of causal effects of the built environment on travel behavior from a cross-sectional approach.

9.1.1 Estimation of a causal mechanism between changes in built environment characteristics and changes in trip frequencies by mode

Using a panel dataset of new-movers to a high density mixed-use development in Kashiwanoha area in Chiba prefecture, analysis findings suggest that conditional on the strict exogeneity assumption, the existence of a causal mechanism between

- A positive change in the number of potential activity opportunities within one's neighborhood and positive changes in the frequency of non-work activities conducted nearby and reached by non-motorized modes.
- A positive change in the number of potential activity opportunities within one's neighborhood and negative changes in the frequency of non-work activities conducted faraway by car.

In other words, findings suggest the existence of a causal mode substitution mechanism between nearby activities reached by non-motorized modes and faraway activities reached by car for some non-work activities.

9.1.2 Operationalization of a continuous index to measure urbanization level

An operationalization method was proposed to quantify built environment characteristics under a single index variable. This index was specified as a latent variable model and estimated via Confirmatory Factor Analysis, which (in spite of limitations) allows for the calculation of goodness of fit statistics to test how well the estimated solution reproduces the observed variances and covariances of indicators (Brown, 2006). This index can then be used as a continuous treatment variable in propensity score estimations of causal effects using cross-sectional data.

9.1.3 Implementation and validation of a methodology to assess the causality problem from a cross-sectional approach

Although requiring stronger assumptions than those made in the panel data case (strong ignorability of treatment), a propensity score approach under continuous treatments was implemented to estimate casual effects of the built environment and travel behavior. To the best of our knowledge, this is the first application of its kind in the planning literature. This approach relaxes the binary treatment assumption of the traditional propensity score approaches which polarize the built environment into two extremes (e.g. urban vs suburban), thus allowing for a more precise understanding of the built environment effect on travel behavior at all levels of the urbanization spectrum.

The effectiveness of the proposed methodology in reducing bias against OLS was validated via Monte Carlo simulation using different data generating processes. As far as the literature reviewed in Chapter 2 is concerned, no other study has attempted to validate the effectiveness of the propensity score estimates against other methodologies.

9.1.4 Estimation of causal effects of the built environment on travel behavior from a cross-sectional perspective

Under the strong ignorability of treatment assumption, casual effects of urbanization level on non-work trip frequency (maintenance and discretionary) were estimated where

- An increase in urbanization level, as measured by the urbanization index, has a negative effect on non-work home-based car trip frequencies.
- An increase in urbanization level as measured by the urbanization index, has a positive effect on non-work home based non-motorized trip frequencies.

In other words, findings suggest the existence of a causal mode substitution mechanism between car and non-motorized modes given increases in the urbanization level at residential location.

9.2 POLICY IMPLICATIONS

In general, findings support the notion that the built environment has a significant effect on travel behavior, specifically, on trip frequency by mode, providing some empirical evidence to the claims of compact city advocates. As the Kashiwa case study illustrated, even after controlling for residential self-selection, retrofitting suburban areas with compact developments might be successful in reducing faraway non-work car trips and consequently increasing nearby non-motorized trips. This is a non-trivial issue considering the challenges that Japan faces as a super-aged nation. Data from Hiroshima and Fukuoka city also support the notion that living in more urbanized areas is conducive to less car use and more non-motorized trips.

Nevertheless, it is important to note that the issue at hand is more complex that just retrofitting or promoting a certain (re)development model. In spite of the existence of a causal relation, residential location not only is a self-selecting process guided by household life-stage, lifestyle and preferences, but it's at the same time constrained by the supply and demand dynamics of the real estate market. In that sense, a mismatch between supply and demand might hamper efforts to promote compact city paradigms. Even for households that wish to move to the city center, rent costs might be prohibitively expensive, pushing households to more suburban areas where they can afford more space. In the case of Japanese cities, this problem is extenuated by lax urban control laws that allow development to expand even beyond the so called Urban Control Areas, thus promoting suburbanization, perhaps unintentionally.

9.3 LIMITATIONS AND FURTHER RESEARCH

9.3.1 Panel data analysis

In terms of the panel data analysis, two main limitations were identified. First, the effective sample size was rather small, an especially important issue in the case of fixed effect models when considering the issue of reduced variability. Second, regarding external validity of results, given the nature of the study, inferences might only be drawn for a specific socio-economic bracket and for

specific changes in the built environment. Finally, attitudes and preferences were 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. Another important assumption was that conditional on covariates, there will be no difference in the means between treated and untreated groups. This assumption is based on the premise that travel behavior is stable in unchanged decision contexts and/or in the presence of strong habits.

To address this limitations it is recommended that (i) the survey contains a control group of non-movers, (ii) attitudes and preference variables are measured before and after relocation, and (iii) test different types of treatment (i.e. relocation to different environment with distinct built environment characteristic).

9.3.2 Cross-sectional data analysis

In terms of the propensity score approach implemented to assess causality using cross-sectional data, it is stressed yet again that the strong ignorability of treatment assumption is key to establish causality. This highlights the importance that must be placed when specifying the propensity score function, as gross misspecification of the function can result in serious bias (Imai & van Dyk, 2004). In that sense, further research efforts should be directed towards improving the propensity score estimates.

9.3.3 Attitudes measurement and use as control variable

The attitudes and preference issue is one that remains unresolved yet. Although a great number of studies 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), and the extent to which the rather diverse set of existing measures actually capture the self-selection effect remains undefined. As pointed out in Section 8.2.3, even with the same instrument, the number of extracted factors in the Fukuoka solution was different from the number of extracted factors in the

Hiroshima solution. Furthermore, attitudes and preference variables were estimated using principal component analysis (PCA), which does not provides any goodness of fit statistics to evaluate the modes. In that sense, neither model could be validated by using more robust methods such as confirmatory factor analysis. Research efforts should thus be directed towards the development of a theory that guides the attitudes and preference measurements in the planning field.

9.3.4 Assessing other dimensions of travel behavior

The main travel behavior dimension analyzed in this study relate to trip frequencies by mode. However, other relevant dimensions should be analyzed to strengthen the conclusions presented in this dissertation. Certainly the propensity score approach presented here can be used to analyze continuous variables such as travel distance, or fuel consumption, provided reliable data is available.

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APPENDIX

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「パークシティ柏の葉キャンパス一番街」へ転居される方の交通行動･生活行動に関する調査

世帯票

この【世帯票】はなるべく柏の葉への転居をお決めになった方ご本人がご回答ください。

交通手段の保有についてお伺いいたします

問１：あなたのご家庭では現在何台の自動車・バイク（原付含む）・自転車をお持ちですか。〔　〕内に数字をご記入ください。保有していない場合は「０」とご記入ください。

自動車〔　　〕台　　バイク（原付含む）〔　　〕台　　自転車〔　　〕台

問２：現在自動車を保有している方のみにお伺いいたします。それ以外の方は次の問３にお進みください。
ひと月の自動車の世帯全体の燃料代（バイク、原付の燃料代は除く）はいくらくらいですか。

世帯全体で自動車の燃料代がひと月に〔　　〕円くらい

問３：転居後、あなたのご家庭では自動車を保有する予定ですか。番号に○をつけてください。また「１：保有するつもりだ」に○をつけた方は現段階での保有予定の台数も〔　〕内に数字でご記入ください。

１：保有するつもりだ → 転居後に〔　　〕台保有予定　　２：保有しないつもりだ

現在お住まいの場所と柏の葉地区の交通環境についてお伺いいたします

問４：現在の場所にお住まいになってから何年が経ちますか。

〔　　〕年

問５：自宅最寄りの鉄道駅とそこまでの所要時間をお答えください。所要時間は、あなたが最寄り駅まで行くのに最もよく利用する交通機関を〔自動車・バイク・バス・自転車・徒歩〕の中から１つ選んで○をつけ、それを利用した場合の所要時間をお答えください。

〔　　〕線〔　　〕駅まで〔自動車・バイク・バス・自転車・徒歩〕で〔　　〕分

１つ選んで○をつけてください

問６：現在お住まいの場所と転居先である柏の葉地区はそれぞれ、ご家族全体の生活を考えた時に自動車がどの程度必要なところだと思いますか。選択肢から当てはまるものを１つずつ選び、○をつけてください。

＜選択肢＞
１：自動車がないととても不便で暮らしてゆけない場所だ
２：自動車がないと不便だが、暮らしていけないほどではない場所だ
３：自動車がなくてもそれほど不便だと思わない場所だ
４：自動車は不要な場所だ（なくても全く不便を感じない）

現在お住まいの場所は〔１・２・３・４〕
柏の葉地区は　　〔１・２・３・４〕

転居をお決めになった理由等についてお伺いいたします

問７：転居しようと考えたきっかけは何ですか。当てはまる番号すべてに○をつけてください。

１： 子供の誕生・成長	12： 子供の教育環境・子育て環境の問題
２： 親と、または子供との同居	13： 緑地・自然・公園が周囲に足りない
３： 親と、または子供との世帯の分離	14： 東京都心まで遠い
４： 結婚	15： 騒音・振動・悪臭等の公害問題
５： 入学	16： 現在の通学先への通学が不便
６： 通学先の変更（転校、通学先ｷｬﾝﾊﾟｽの変更など）	17： 現在の通勤先への通勤が不便
７： 就職	18： 鉄道駅まで遠い
８： 通勤先の変更（転勤、転職など）	19： 買物などの日常生活が不便
９： 退職、離職	20： 車がないと暮せない場所だから
10： 現在お住まいの家自体への不満（狭いなど）	21： 特に不満は無かったが引越しをしたかったから
11： 駐車場が家から遠い	22： 当マンションに住みたいと思ったから

・その他特にきっかけがありましたら、以下の空欄に具体的にご記入ください。

問８：転居先を選ぶにあたり、次の各項目をどの程度重視しましたか。また現時点で、柏の葉地区の当マンションでそれがどの程度満たされるとお考えですか。回答例にならってそれぞれ○をつけてください。

(※１)：ご家族に通学する方がいない場合、この項目への回答は不要です
(※２)：ご家族に通勤する方がいない場合、この項目への回答は不要です

項目	重視の度合い				満足の度合い			
	大変重視した	やや重視した	あまり重視しなかった	全く重視しなかった	大変満足できそう	やや満足できそう	あまり満足できなさそう	全く満足できなさそう
【回答例】通学の便	1	2	3	4	1	2	3	4
買物などの日常生活の便	1	2	3	4	1	2	3	4
鉄道駅までの近さ	1	2	3	4	1	2	3	4
東京都心までの近さ	1	2	3	4	1	2	3	4
住宅の質の高さ	1	2	3	4	1	2	3	4
周辺の自然環境	1	2	3	4	1	2	3	4
価格	1	2	3	4	1	2	3	4
住宅の広さ	1	2	3	4	1	2	3	4
自動車がなくても暮らせる	1	2	3	4	1	2	3	4
（※１）通学の便	1	2	3	4	1	2	3	4
（※２）通勤の便	1	2	3	4	1	2	3	4

・その他特に重視した点がありましたら、以下の空欄に具体的にご記入ください。

問９：柏の葉地区では、街づくりのコンセプトとして「知」「健康」「緑」「環境」を挙げています。

知　：東大や千葉大による大学主催の公開講座。大学と連携した街づくりが行われている。
健康：広い歩道でサイクリングやランニング。柏の葉公園でのテニスなど健康づくりを応援。
緑　：こんぶくろ池・柏の葉公園などなど周辺には緑がいっぱい。
環境：生ごみの堆肥化・太陽光の活用など環境にやさしい街づくりを推進。

これらのコンセプトは柏の葉地区への転居を決める上でどの程度影響しましたか。各項目について、以下の表の当てはまる番号に○をつけてください。

項目	大きく影響した	やや影響した	あまり影響しなかった	全く影響しなかった	知らなかった
知	1	2	3	4	5
健康	1	2	3	4	5
緑	1	2	3	4	5
環境	1	2	3	4	5

ご家族についてお伺いいたします

問 10：現在同居されているご家族全員について、下表に「例」にならってご記入ください。なお、この【世帯票】を記入されているご自身をＡにご記入ください。

このアンケートに回答されている方をＡに

記号	続柄	年齢	性別	自動車免許	現在の職業	柏の葉地区への転居
【例】		歳	男・女	有・無		する・しない
A		歳	男・女	有・無		する・しない
B		歳	男・女	有・無		する・しない
C		歳	男・女	有・無		する・しない
D		歳	男・女	有・無		する・しない
E		歳	男・女	有・無		する・しない
F		歳	男・女	有・無		する・しない
G		歳	男・女	有・無		する・しない
H		歳	男・女	有・無		する・しない

右の「職業表」から選んで番号でお答えください

問 11：現在同居されている家族以外の方で、当マンションに転居後に同居する予定の方はいらっしゃいますか。以下の表にご記入ください。「現在の職業」は問 10 と同様に右の職業表から選んで番号でお答えください。

記号	年齢	性別	自動車免許	現在の職業	記号	年齢	性別	自動車免許	現在の職業
1	歳	男・女	有・無		3	歳	男・女	有・無	
2	歳	男・女	有・無		4	歳	男・女	有・無	

右の「職業表」から選んで番号でお答えください

■GPS 携帯を用いたプローブパーソン調査への参加のお願い■

さらに、ご家族の皆様の詳細な移動軌跡と生活行動のデータを採取させていただく目的で、GPS 携帯を２ヶ月間所持していただくとともに Web 上で日誌をつけていただく「プローブパーソン調査」への協力世帯を募集しております。謝礼は１世帯につき３万円です。調査期間は 10 月 1 日～11 月 30 日を予定しております。よろしければご参加いただけませんでしょうか。以下のいずれかに○をつけてください。

ぜひ参加したい　・　参加してもよい　・　参加したくない

※「ぜひ参加したい」「参加してもよい」に○をつけられた方は、連絡用の電話番号またはメールアドレスをご記入ください。

電話番号 または メールアドレス

■謝礼のクオカードと２回目のアンケート調査票をお送りする際に利用いたします。忘れずにご記入ください。

・ご住所

(〒　　―　　)

・お名前

様

ご回答ありがとうございました。
引き続き【個人票】の記入にもご協力ください。

番号	職業表	
1	農林漁業従事者	農耕・牧畜作業員・植木職・造園職・漁師・漁船の船長船員・水産養殖作業者など
2	技能工・生産工程従事者	各種製品製造・修理作業者・料理人以外の各種職人・大工・土木作業員・自動車整備工・製図工・印刷工・美術工芸工・工作機械工・板金工など
3	販売従事者	店員・行商人・外交員・仲介人・店主・セールスマンなど
4	サービス業従事者	家政婦・理容師・ウェイトレス・料理人・清掃員・アパート管理人など
5	運輸・通信従事者	運転手・車掌・通信士・交換手・郵便配達人・漁船以外の船長船員など
6	保安職業従事者	自衛官・警察官・消防員・ガードマン・看守・守衛・海上保安員など
7	事務的職業従事者	一般事務員・集金人・キーパンチャー・会計事務員・検針員・電子計算機械操作員など
8	技術・専門的職業従事者	研究者・技術者・医師・看護士・栄養士・会計士・弁護士・宗教家・芸術家・美術家・教師・保母・記者・職業スポーツ家・デザイナーなど
9	管理的職業従事者	もっぱら事業の経営、管理の業務にあたる人（課長職以上、小売卸売店の店長、駅長、郵便局長、工場長、議員など）
10	その他職業	これらの職業に分類されない方
11	生徒・児童・園児	保育園児・幼稚園児・小学生・中学生
12	学生	高校生・専門学生・大学生・大学院生・予備校生・各種学校生（職業従事者を除く）など
13	主婦	主婦（パートタイマーなどの職業従事者を除く）
14	無職・その他	特定の職についていない方・1ヶ月以上の休職者の方など

※この職業分類は国勢調査と同様の分類方法を用いております。

「パークシティ柏の葉キャンパス一番街」へ転居される方の交通行動･生活行動に関する調査

個人票

ご協力ありがとうございます

問０：あなたは　【世帯票】問 10　のＡ～Ｈのうちどなたですか。
当てはまる記号に○をつけてください。

Ａ　Ｂ　Ｃ　Ｄ　Ｅ　Ｆ　Ｇ　Ｈ

現在と将来の通勤通学についてお伺いいたします

問１：あなたは現在通勤・通学していますか。また、転居後に通勤・通学する予定ですか。現在通勤・通学している方はその頻度、通勤・通学先、所要時間、交通手段を、転居後に通勤・通学する予定の方は転居後のそれら（分かる範囲で結構です）を、下の表にご記入ください。※パートタイムへの通勤も「通勤」に含めます

通勤・通学		通勤・通学頻度	通勤・通学先住所（「○丁目」までで結構です）	交通手段	所要時間
【例】	している　していない	週　　日			分
現在	している　していない	週　　日			分
転居後	する　しない　未定	週　　日			分

※通勤先が複数ある場合は最もよく行く場所についてお答えください

交通手段選択肢			
	１：鉄道	５：バイク・原付	※「交通手段欄」の記入法　：例えば・・家から駅まで「2:バス」で行き、駅から「1:鉄道」を使い、駅から「7:徒歩」で目的地に着く場合「２→１→７」とお書きください
	２：バス	６：自転車	
	３：自動車（自分で運転）	７：徒歩	
	４：自動車（送迎）	８：その他	

問２：現在、通勤・通学されている方にお伺いいたします。それ以外の方は次の問３にお進みください。
勤務時間・在学時間は決まっていますか。当てはまる番号に○をつけてください。

１：完全に不定期（シフト制勤務など、日によって時間が大きく異なる場合）
２：ある程度決まっている（２に○をつけた方は、時間もご記入ください↓）
〔　　〕時〔　　〕分ごろ職場・学校に到着し、〔　　〕時〔　　〕分ごろ職場・学校を離れる

活動への興味と実行の程度についてお伺いいたします

問３：以下に挙げる活動に関して、あなたはどの程度興味があり、どの程度実行していますか。回答例にならって当てはまる番号に○をつけてください。

活動の内容		興味の程度				実行の程度			
		大変興味ある	やや興味ある	あまり興味ない	全く興味ない	よく行う	たまに行う	あまり行わない	全く行わない
【回答例】	：読書をする事	1	2	3	4	1	2	3	4
あ	セミナーや公開講座に参加する事	1	2	3	4	1	2	3	4
い	図書館に行く事	1	2	3	4	1	2	3	4
う	公園緑地でのんびりする事	1	2	3	4	1	2	3	4
え	運動する事	1	2	3	4	1	2	3	4
お	ｸﾗﾌﾞ、ｻｰｸﾙ、NPO活動をする事	1	2	3	4	1	2	3	4
か	環境問題に関する知識を得る事	1	2	3	4	1	2	3	4
き	街づくりに参加する事	1	2	3	4	1	2	3	4
く	緑を育てる事	1	2	3	4	1	2	3	4
け	環境を意識した行動をとる事	1	2	3	4	1	2	3	4
こ	健康に関する知識を得る事	1	2	3	4	1	2	3	4

問４：問３の各活動「あ」～「こ」の中で、あなたが一番よく行う活動はどれですか。１つに○をつけてください。
どの活動も行わないという場合は、「どの活動も行わない」に○をつけてください。

あ	い	う	え	お	か	き	く	け	こ	どの活動も行わない

問５：問４で「あ」～「お」に○をつけた方にお伺いいたします。それ以外の方は問６にお進みください。
あなたが○をつけた「一番よく行う活動」をよく行う場所・施設の名称と、そこで活動を行う頻度について、回答例にならって３ヵ所以内でお答えください。なお、特に活動場所・施設が決まっていない場合には、最近その活動を行った場所の名称を３ヵ所以内でお答えください（その場合、「そこでの活動頻度」欄のご回答は不要です）。

	活動場所・施設の名称	そこでの活動頻度	
回答欄		週　月 年　回程度	※　活動場所・施設の名称の記入について ・場所の名称は、だいたいの位置が分かるようになるべく具体的にご記入下さい 例（×：ｺﾅﾐｽﾎﾟｰﾂｸﾗﾌﾞ　○：津田沼のｺﾅﾐｽﾎﾟｰﾂｸﾗﾌﾞ） ・場所の名称が分からない、または名称が無い場合はその場所を示す代表的な名前でお答え下さい 例（渋谷、自宅近所）
		週　月 年　回程度	
		週　月 年　回程度	
回答例		週　月 年　回程度	問４で選んだ記号「え：運動する事」 ・自宅近所で週3回程度ランニングをする ・○×スポーツクラブ△△店に週1回程度行く ・××市市営プールに月1回程度行く
		週　月 年　回程度	
		週　月 年　回程度	

現在のあなたの意識についてお伺いいたします

問６：下記の各問いに対し直感的にお答えください。

評価	とても そう思う		←	どちら ともい えない	→		全くそう 思わない
徒歩での移動は好きだ	1	2	3	4	5	6	7
普段環境問題を気にしている	1	2	3	4	5	6	7
鉄道での移動が好きだ	1	2	3	4	5	6	7
将来のために今健康に配慮する事が大切だ	1	2	3	4	5	6	7
クルマでの移動が好きだ	1	2	3	4	5	6	7
健康に配慮すべきだ	1	2	3	4	5	6	7
バスでの移動が好きだ	1	2	3	4	5	6	7
環境問題に配慮すべきだ	1	2	3	4	5	6	7
普段から健康を気にしている	1	2	3	4	5	6	7
一人一人が環境に配慮する事が必要だ	1	2	3	4	5	6	7
自転車での移動が好きだ	1	2	3	4	5	6	7
休日は家にいるのが好きだ	1	2	3	4	5	6	7
自分は社交的なほうである	1	2	3	4	5	6	7

現在の自動車利用形態についてお伺いいたします

問７：ご家族の中での現在のあなたの自動車利用形態について、当てはまる番号１つに○をつけてください。
１または２を選択された方は、自動車を日常的に運転するようになってから経つ年数もお答えください。

１：（ほぼ）自分専用の自家用車を持っている　⇒自動車を日常的に運転して〔　　〕年程度
２：家族共有の自家用車があり主に運転する役目だ　⇒自動車を日常的に運転して〔　　〕年程度
３：家族共用の自家用車があり、主に家族の運転に同乗する側だ
４：（自分でも家族でも）自家用車は所持していない

※ 日常的とは、自動車を週１日以上使う事とお考え下さい

あなたが *自宅の外で* 行う活動の頻度や場所についてお伺いいたします

問８：あなたが<u>ご自宅の近所（徒歩や自転車で 20 分程度で行ける範囲）</u>でよく行う活動について、以下の表の「近所」の□に✓してください。同様に、あなたが<u>ご自宅から遠方（徒歩や自転車で 20 分程度では行けない範囲）</u>でよく行う活動について、以下の表の「遠方」の□に✓してください

余暇/娯楽	近所	遠方	買物（「見るだけ」も含む）	近所	遠方
【回答例】映画を見る	□	□	【回答例】電化製品を買う	□	□
映画を見る	□	□	食料品・日用品を買う	□	□
散歩をする	□	□	服・雑貨を買う	□	□
友人・親戚と会う	□	□	CD・DVDをレンタルする	□	□
運動する	□	□	書籍・CD・DVDを買う	□	□
公園・緑地で憩う	□	□	電化製品を買う	□	□
学習	**近所**	**遠方**	**飲食**	**近所**	**遠方**
図書館で本を借りる	□	□	レストラン・食堂で食事をする	□	□
英会話等のスクールに通う	□	□	喫茶店でお茶・コーヒーを飲む	□	□
講演会・勉強会に出席する	□	□	居酒屋・バーでお酒を飲む	□	□
習い事をする	□	□			

問９：以下の表の各活動を、<u>ご自宅の近所（徒歩や自転車で 20 分程度で行ける範囲）</u>と<u>ご自宅から遠方（徒歩や自転車で 20 分程度では行けない範囲）</u>でそれぞれ何回程度、どの交通手段を利用して行っていますか。

■通勤（パートへの通勤も含みます）・通学されている方

活動回数を「<u>A：仕事・学校のない日／仕事・学校からの帰宅後</u>」と「<u>B：仕事・学校への行き帰り時</u>」に分けてご記入ください。「A」については利用する<u>交通手段</u>もご記入ください。

■通勤・通学されていない方

トータルの活動回数を「<u>A：仕事・学校のない日／仕事・学校からの帰宅後</u>」欄にご記入ください。また、利用する<u>交通手段</u>もご記入ください。なお、「<u>B：仕事・学校への行き帰り時</u>」欄は空欄で結構です。

活動内容		活動場所	A:仕事・学校のない日／仕事・学校からの帰宅後				B:仕事・学校への行き帰り時
			頻度	交通手段 車バイク	交通手段 自転車徒歩	交通手段 公共交通	頻度
余暇/娯楽	映画，散歩，友人・親戚との面会，行楽，運動，近所でのジョギング等	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
買物	通常の買物，レンタル等 ※駅売店や自販機などでの軽微な買物は除く	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
学習 ※通学先の学校での学習は除きます	図書館，英会話等の各種スクール，講演会・勉強会等	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
飲食	食堂，レストラン，喫茶店，バー，居酒屋等での飲食	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度

回答例								
	通勤通学している方	買物	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		近所で「A：<u>仕事のない日／帰宅後</u>」に買物を<u>週４回</u>程度（<u>うち３回は自動車、１回は徒歩</u>） 「B：<u>仕事への行き帰り</u>」に買物を<u>週３回</u>程度する						
	通勤通学されていない方	買物	近所	週　月 年　回程度	回	回	回	週　月 年　回程度 記入不要
		近所で 買物を<u>週４回</u>程度（<u>うち３回は自動車、１回はバス</u>）する						

問 10： ご自宅から遠方（徒歩や自転車で 20 分程度では行けない範囲）で、「余暇/娯楽」、「買物」、「学習」、「飲食」の４つの活動をよく行う場所はどこですか。思いつく場所を 10 ヶ所以内で挙げ、その場所の名称、来訪日数、活動内容、交通手段、所要時間について、下の記入例にならってご回答ください。

■記入方法■

【場所の名称について】

・渋谷でショッピング、○○駅の駅前で買物、ヤマダ電機○○店周辺など活動場所が面的に広がっている場合
⇒その場所を示す代表的な名前（渋谷、○○駅前、ヤマダ電機○○店周辺）でお答えください

・ショッピングセンター・友人宅・劇場など、活動場所が特定の施設・場所である場合
⇒具体的な施設の名称（イオン○○店、○○駅付近の友人宅）で、大体の場所が分かるようにお答えください。

【来訪頻度について】

通勤通学されていない方は「そのうち仕事・学校の行き帰りに寄る頻度」欄は記入不要です

場所の名称	来訪頻度		活動内容	家からそこまで直接行くとすると…	
	全来訪頻度	そのうち仕事・学校の行き帰りに寄る頻度	あてはまるものを全て選んで○をつけてください	利用する主な交通手段 選択肢から１つ選択して○をつけてください	その場合の所要時間
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分

回答例

通勤・通学している方	ジャスコ柏店	週　月　年　回程度	回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	ジャスコ柏店に週５回、うち３回は仕事帰りに行く。目的は買物。家からジャスコ柏店まで行く場合は自動車で、その場合の時間は約25分で到着する					
通勤・通学されていない方	渋谷	週　月　年　回程度	記入不要 回	余暇/娯楽　買物　学習　飲食	自動車　バイク　自転車　鉄道　バス　徒歩	分
	渋谷に週２回行く。目的は買物と余暇/娯楽。家から渋谷まで行く場合は鉄道で、その場合の時間は約50分で到着する					

第３回	「パークシティ柏の葉キャンパス一番街」へ転居された方の 転居後の交通行動・生活行動に関する調査	世帯票

この【世帯票】はなるべく柏の葉への転居をお決めになった方ご本人様がご回答ください。

交通手段の保有についてお伺いいたします

問１：あなたのご家庭では現在何台の自動車・バイク（原付含む）・自転車をお持ちですか。〔　〕内に数字をご記入ください。保有していない場合は「０」とご記入ください。

自動車〔　　〕台　　バイク（原付含む）〔　　〕台　　自転車〔　　〕台

柏の葉地区の交通環境についてお伺いいたします

問２：実際に柏の葉地区の当マンションに住んでみて、ご家族全体が生活していく上で自動車がどの程度必要なところだと感じていますか。選択肢から当てはまるものを１つ選び、○をつけてください。

＜選択肢＞
１：自動車がないととても不便で暮らしてゆけない場所だ
２：自動車がないと不便だが、暮らしていけないほどではない場所だ
３：自動車がなくてもそれほど不便だと思わない場所だ
４：自動車は不要な場所だ（なくても全く不便を感じない）

柏の葉地区の住環境についてお伺いいたします

問３：実際に柏の葉地区の当マンションに住んでみて、次の各項目がどの程度満たされていると感じていますか。回答例にならってそれぞれ○をつけてください。

(※１)：ご家族に通学される方がいない場合、この項目への回答は不要です
(※２)：ご家族に通勤される方がいない場合、この項目への回答は不要です

項目	満足の度合い			
	大変満足	やや満足	やや不満	大変不満
【回答例】通学の便	1	2	3	4
買物などの日常生活の便	1	2	3	4
鉄道駅までの近さ	1	2	3	4
東京都心までの近さ	1	2	3	4
住宅の質の高さ	1	2	3	4
周辺の自然環境	1	2	3	4
価格	1	2	3	4
住宅の広さ	1	2	3	4
自動車がなくても暮らせる	1	2	3	4
（※１）通学の便	1	2	3	4
（※２）通勤の便	1	2	3	4

・その他、住環境に関して感じておられることをご自由にご記入下さい。

ご家族についてお伺いいたします

問４：当マンションにお住まいのご家族のうち、**第１回アンケート調査の個人票にご回答いただいた方**の情報（の一部、年齢は＋１歳としています）を以下に記しています。**「年齢」欄・「訂正」欄にご記入頂く**と同時に、記載箇所に関して**現在の状況と相違する箇所がございましたら、訂正ないし追加記入をお願いいたします。**

記号	続柄	年齢	性別	自動車免許	現在の職業	訂正
【例】	ご主人様	５６ 歳	(男)・女	有・(無)	6	あり・なし
A		歳	男・女	有・無		あり・なし
B		歳	男・女	有・無		あり・なし
C		歳	男・女	有・無		あり・なし
D		歳	男・女	有・無		あり・なし
E		歳	男・女	有・無		あり・なし
F		歳	男・女	有・無		あり・なし

確認のため、必ずご回答下さい

訂正・追加記入の場合、下記の「職業表」から選んで**番号で**お答え下さい

番号	職業表	
1	農林漁業従事者	農耕・牧畜作業員・植木職・造園職・漁師・漁船の船長船員・水産養殖作業者など
2	技能工・生産工程従事者	各種製品製造・修理作業者・料理人以外の各種職人・大工・土木作業員・自動車整備工・製図工・印刷工・美術工芸工・工作機械工・板金工など
3	販売従事者	店員・行商人・外交員・仲介人・店主・セールスマンなど
4	サービス業従事者	家政婦・理容師・ウェイトレス・料理人・清掃員・アパート管理人など
5	運輸・通信従事者	運転手・車掌・通信士・交換手・郵便配達人・漁船以外の船長船員など
6	保安職業従事者	自衛官・警察官・消防員・ガードマン・看守・守衛・海上保安員など
7	事務的職業従事者	一般事務員・集金人・キーパンチャー・会計事務員・検針員・電子計算機械操作員など
8	技術・専門的職業従事者	研究者・技術者・医師・看護士・栄養士・会計士・弁護士・宗教家・芸術家・美術家・教師・保母・記者・職業スポーツ家・デザイナーなど
9	管理的職業従事者	もっぱら事業の経営、管理の業務にあたる人（課長職以上、小売卸売店の店長、駅長、郵便局長、工場長、議員など）
10	その他職業	これらの職業に分類されない方
11	生徒・児童・園児	保育園児・幼稚園児・小学生・中学生
12	学生	高校生・専門学生・大学生・大学院生・予備校生・各種学校生（職業従事者を除く）など
13	主婦	主婦（パートタイマーなどの職業従事者を除く）
14	無職・その他	特定の職についていない方・1ヶ月以上の休職者の方など

※この職業分類は国勢調査と同様の分類方法を用いております。

ご協力ありがとうございました。引き続き、個人票のご記入にご協力下さい。
また、謝礼をお送りするため、以下に新住所とご芳名のご記入をお願いいたします。

〒277-0871　千葉県柏市若柴 173-8　柏の葉キャンパス 151 街区

パークシティ柏の葉キャンパス一番街 ＿＿＿－＿＿＿＿＿　（ご芳名）＿＿＿＿＿＿＿＿＿＿

第３回	「パークシティ柏の葉キャンパス一番街」へ転居された方の 転居後の交通行動・生活行動に関する調査	個人票

ご協力ありがとうございます

こちらの回答用紙は **B　奥　様** 用です。お間違えの無い様にご注意ください。

現在の 通勤通学 についてお伺いいたします

問１：あなたは現在通勤・通学していますか。通勤・通学している方はその頻度、通勤・通学先、主な交通手段、所要時間を、下の表にご記入ください。　※パートタイムへの通勤も「通勤」に含めます

通勤・通学 （いずれかに○）	通勤・通学 頻度	通勤・通学先住所 （「○丁目」までで結構です）	主な交通手段	所要時間
している　　していない	週　　日			分

現在の 自動車利用形態 についてお伺いいたします

問２：ご家族の中での現在のあなたの自動車利用形態について、当てはまる番号１つに○をつけてください。
１または２を選択された方は、自動車を日常的に運転するようになってから経つ年数もお答えください。

１：（ほぼ）自分専用の自家用車を持っている　⇒自動車を日常的に運転して〔　　〕年程度
２：家族共有の自家用車があり主に運転する役目だ　⇒自動車を日常的に運転して〔　　〕年程度
３：家族共用の自家用車があり、主に家族の運転に同乗する側だ
４：（自分でも家族でも）自家用車は所持していない

※ 日常的とは、自動車を週１日以上使う事とお考え下さい

活動への興味 と 実行の程度についてお伺いいたします

問３：以下に挙げる活動に関して、あなたはどの程度興味があり、どの程度実行していますか。回答例にならって当てはまる番号に○をつけてください。

活動の内容	活動に対する興味の程度				活動の実行頻度			
	大変興味ある	やや興味ある	あまり興味ない	全く興味ない	よく行う	たまに行う	あまり行わない	全く行わない
回答例	1	(2)	3	4	(1)	2	3	4
セミナーや公開講座に参加する事	1	2	3	4	1	2	3	4
図書館に行く事	1	2	3	4	1	2	3	4
公園緑地でのんびりする事	1	2	3	4	1	2	3	4
運動する事	1	2	3	4	1	2	3	4
クラブ、サークル、NPO 活動をする事	1	2	3	4	1	2	3	4
環境問題に関する知識を得る事	1	2	3	4	1	2	3	4
街づくりに参加する事	1	2	3	4	1	2	3	4
緑を育てる事	1	2	3	4	1	2	3	4
環境を意識した行動をとる事	1	2	3	4	1	2	3	4
健康に関する知識を得る事	1	2	3	4	1	2	3	4

現在のあなたの 意識 についてお伺いいたします

問４：下記の各問いに対しそれぞれ直感的に、あなたの考えに当てはまるもの１つに○をつけてください。

評価	とても そう思う	←	←	どちらとも いえない	→	→	全くそう 思わない
用事はなるべく近くで済ませたい	1	2	3	4	5	6	7
徒歩での移動は好きだ	1	2	3	4	5	6	7
普段環境問題を気にしている	1	2	3	4	5	6	7
鉄道での移動が好きだ	1	2	3	4	5	6	7
将来のために今健康に配慮する事が大切だ	1	2	3	4	5	6	7
クルマでの移動が好きだ	1	2	3	4	5	6	7
健康に配慮すべきだ	1	2	3	4	5	6	7
お気に入りの場所に繰り返し通いたい	1	2	3	4	5	6	7
バスでの移動が好きだ	1	2	3	4	5	6	7
環境問題に配慮すべきだ	1	2	3	4	5	6	7
色々なところに行ってみたい	1	2	3	4	5	6	7
普段から健康を気にしている	1	2	3	4	5	6	7
一人一人が環境に配慮することが必要だ	1	2	3	4	5	6	7
自転車での移動が好きだ	1	2	3	4	5	6	7
よりよい場所があれば遠くてもそこに行きたい	1	2	3	4	5	6	7

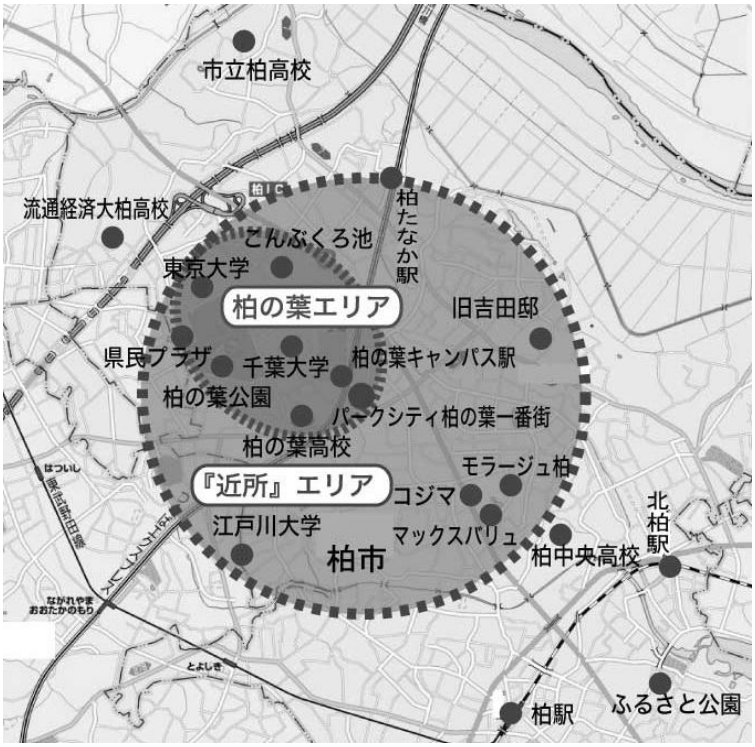
あなたが ご自宅の*近所／遠方で* 行う活動の種類についてお伺いいたします

問５：あなたがご自宅の「近所」（右下図参照）でよく行う活動について、以下の表の「近所」の□に✓して下さい。
同様に、あなたがご自宅の「遠方」でよく行う活動について、以下の表の「遠方」の□に✓して下さい。

【チェック欄】

余暇/娯楽	近所	遠方
【回答例】映画を見る	☑	□
映画を見る	□	□
散歩をする	□	□
友人・親戚と会う	□	□
運動する	□	□
公園・緑地で憩う	□	□
学習	**近所**	**遠方**
図書館で本を借りる	□	□
英会話等のスクールに通う	□	□
講演会・勉強会に出席する	□	□
習い事をする	□	□
買物（「見るだけ」も含む）	**近所**	**遠方**
食料品・日用品を買う	□	□
服・雑貨を買う	□	□
CD・DVD をレンタルする	□	□
書籍・CD・DVD を買う	□	□
電化製品を買う	□	□
飲食	**近所**	**遠方**
レストラン・食堂で食事をする	□	□
喫茶店でお茶・コーヒーを飲む	□	□
居酒屋・バーでお酒を飲む	□	□

【「近所」のエリアと柏の葉エリア】



「近所」：大円内（徒歩ないし自転車で２０分圏内）
「遠方」：「近所」エリアの外側
※　境界は大まかなものです

あなたが *ご自宅の近所／遠方で* 行う活動の頻度・活動場所への交通手段についてお伺いいたします

問６：以下の表の各活動を、**ご自宅の近所**と**遠方（エリアは前問の図に準じます）**でそれぞれ何回程度、どの交通手段を利用して行っていますか。回答例をご参照の上、ご記入下さい。

■通勤（パートへの通勤も含みます）・通学されている方

活動回数を「A：仕事・学校のない日／仕事・学校からの帰宅後」と「B：仕事・学校への行き帰り時」に分けてご記入ください。「A」については利用する交通手段もご記入ください。

■通勤・通学されていない方

トータルの活動回数を「A：仕事・学校のない日／仕事・学校からの帰宅後」欄にご記入ください。また、利用する交通手段もご記入ください。なお、「B：仕事・学校への行き帰り時」欄は空欄で結構です。

回答例	活動内容		活動場所	A:仕事・学校のない日／仕事・学校からの帰宅後 頻度	交通手段 自動車バイク	交通手段 自転車徒歩	交通手段 公共交通	B:仕事・学校への行き帰り時 頻度
	通勤通学している方	買　物	近所	(週)月 年 4 回程度	3 回	1 回	回	(週)月 年 3 回程度
	通勤通学している方	近所で、「仕事のない日／帰宅後」に買物を週４回程度（うち３回は自動車、１回は徒歩利用）、「仕事の行き帰り」に買物を週３回程度する。遠方では買物は殆どしない。						
	通勤通学されていない方	買　物	近所	(週)月 年 3 回程度	2 回	回	1 回	週 月 記入不要 年 回程度
	通勤通学されていない方	買　物	遠方	(週)月 年 2 回程度	回	回	2 回	週 月 記入不要 年 回程度
	通勤通学されていない方	近所で買物を週３回程度（うち２回は自動車、１回はバス）、遠方で買物を週２回程度（２回とも鉄道）する。						

余暇/娯楽	映画，散歩，友人・親戚との面会，行楽，運動，近所でのジョギング等	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
買　物	通常の買物，レンタル等 ※駅売店や自販機などでの軽微な買物は除く	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
学　習 ※通学先の学校での学習は除く	図書館，英会話等の各種スクール，講演会・勉強会等	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
飲　食	食堂，レストラン，喫茶店，バー，居酒屋等での飲食	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度

あなたが *ご自宅の遠方で* 行う活動の頻度と活動を行う場所について、特に詳しくお伺いいたします

問７： あなたが**ご自宅の遠方**で、**「余暇/娯楽」、「買物」、「学習」、「飲食」**の４つの活動をよく行う**場所**はどこですか。思いつく場所を **10 ヶ所以内**で挙げ、その場所の名称、来訪頻度、活動内容、交通手段、所要時間について、下の記入例にならってご回答ください。

■記入方法■

【場所の名称について】

・**○○駅の駅前で買物、ヤマダ電機△△店周辺など活動場所が面的に広がっている場合**
⇒その場所を示す代表的な名前（秋葉原、○○駅前、ヤマダ電機△△店周辺など）でお答え下さい

・**ショッピングセンター・友人宅・劇場など、活動場所が特定の施設・場所である場合**
⇒具体的な施設の名称（イオン□□店、○○駅付近の友人宅）で、**大体の場所が分かるように**お答え下さい。

【来訪頻度について】

通勤通学されていない方は「そのうち仕事・学校の行き帰りに寄る頻度」欄は記入不要です

		場所の名称	来訪頻度		活動内容	家からそこまで直接行くとすると…	
			全来訪頻度	そのうち仕事・学校の行き帰りに寄る頻度	あてはまるものを**全て選んで**○をつけてください	利用する主な交通手段 選択肢から **1つ選択して** ○をつけてください	その場合の所要時間
回答例	通勤・通学している方	ジャスコ柏店	(週) 月 年 **5** 回程度	**3** 回	余暇/娯楽 (買物) 学習 飲食	(自動車) バイク 自転車 鉄道 バス 徒歩	**25** 分
		ジャスコ柏店に週５回、うち３回は仕事帰りに行く。目的は買物。家からジャスコ柏店まで行く場合は自動車で、その場合の時間は約 25 分で到着する。					
	通勤・通学されていない方	渋谷	(週) 月 年 **2** 回程度	記入不要 回	(余暇/娯楽) (買物) 学習 飲食	自動車 バイク 自転車 (鉄道) バス 徒歩	**50** 分
		渋谷に週２回行く。目的は買物と余暇/娯楽。家から渋谷まで行く場合は鉄道で、その場合の時間は約 50 分で到着する。					

	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分
	週 月 年 回程度	回	余暇/娯楽 買物 学習 飲食	自動車 バイク 自転車 鉄道 バス 徒歩	分

あなたが *柏の葉地区内の場所* へ訪れた回数や活動の頻度や場所について、特に詳しくお伺いいたします

問８：柏の葉地区には自転車・徒歩で気軽に訪れることのできる魅力的な場所が幾つも在ります。そのような例として、以前「柏の葉 Walker & Cyclist」にてご紹介した１０箇所の場所について、**転居後に訪れた回数（大まかで構いません）をお答えください。また、その際の主な交通手段を以下１～６よりお選び頂き、番号にてご回答下さい。**

※　公園・池・キャンパスについては、単に通り抜けた回数は除きます。（散歩・サイクリング等で訪れた回数は含みます。）

【交通手段の選択肢】

１．徒歩　　２．自転車　　３．バイク　　４．バス　　５．自動車　　６．その他

【東京大学柏キャンパス】
★見どころ★
緑豊かなキャンパス、ＤＶＤ・本が豊富な図書館、カフェテラスなど
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【柏の葉バッティングスタジアム】
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【こんぶくろ池】
★見どころ★
今も残る本当の自然。
夏は虫が多いですが…。
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【ＳＡＮゴルフセンター】
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【柏の葉公園】
★見どころ★
ドッグラン、茶室「松柏亭」、緑の相談所、テニスコート、フリーマーケットなど
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【ＵＤＣＫ】
★見どころ★
まちの将来像を知る、
まちづくりへの参加など
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【さわやか千葉県民プラザ】
★見どころ★
生涯学習センター、子育てサポートルーム、県民プラザ主催の講演会への参加など
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【ららぽーと柏の葉】
★見どころ★
豊富なショップ群、多方面のクラブ活動、映画館、フィットネス＆スパなど
訪問回数：　週に約＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【エールテニスアカデミー】
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

【千葉大学柏の葉キャンパス】
★見どころ★
農産物の購入、漢方の診療、健康関連の講演会への参加など
訪問回数：＿＿＿＿回
主な交通手段：＿＿＿＿＿＿

問９：あなたは、以下の表の各活動を、**柏の葉地区内**でそれぞれ何回程度、どの交通手段を利用して行っていますか。**以下は問６と同じ回答表ですので、見比べた上で、ご記入をお願い致します**。また、柏の葉地区内の主な施設については、前問をご参照下さい。

活動内容		A:仕事・学校のない日／仕事・学校からの帰宅後				B:仕事・学校への行き帰り時
		頻度	交通手段			頻度
			車 バイク	自転車 徒歩	公共 交通	
余暇/娯楽	映画，散歩，友人・親戚との面会，行楽，運動，近所でのジョギング等	週　月 年　　回程度	回	回	回	週　月 年　　回程度
買物	通常の買物，レンタル等 ※駅売店や自販機などでの軽微な買物は除く	週　月 年　　回程度	回	回	回	週　月 年　　回程度
学習 ※通学先の学校での学習は除く	英会話等の各種スクール，図書館，講演会・勉強会等	週　月 年　　回程度	回	回	回	週　月 年　　回程度
飲食	食堂，レストラン，喫茶店，バー，居酒屋等での飲食	週　月 年　　回程度	回	回	回	週　月 年　　回程度

オンデマンドバス/タクシーや共同自転車に関して、皆様のご意見をお伺いいたします

★ 同封の「オンデマンドバス/タクシー・共同自転車の説明資料」をご覧の上、ご回答下さい。

柏の葉周辺の地域では、共同自転車・オンデマンドバス/タクシーの導入に向けて公・民・学が協力して取り組んでおり、既に両サービスの提供実験が始まっています。**利用したいときに気軽に片道利用**ができる共同自転車、予約をすれば**ドアツードアで目的地まで**運んでくれるオンデマンドバス/タクシーが、近所に行くための交通手段として新たに加われば、柏の葉での生活が一層便利になります。

なお、各サービスの利用料金の目安は次の通りです。（**あくまでも目安です**。）

オンデマンドバス　　：１回あたり 200 円
オンデマンドタクシー　：１回あたり 400 円
　※　タクシー車両で運行しますが、オンデマンドバスと同じく「乗り合い」方式です
共同自転車　：30 分まで無料、以降１時間ごとに 100 円

以上を念頭において、以下の質問にお答え下さい。

問 10：共同自転車やオンデマンドバス/タクシーのサービスが実際に提供されたら、利用してみたいと思いますか。

最も近い感覚のところに、丸をお願いします。

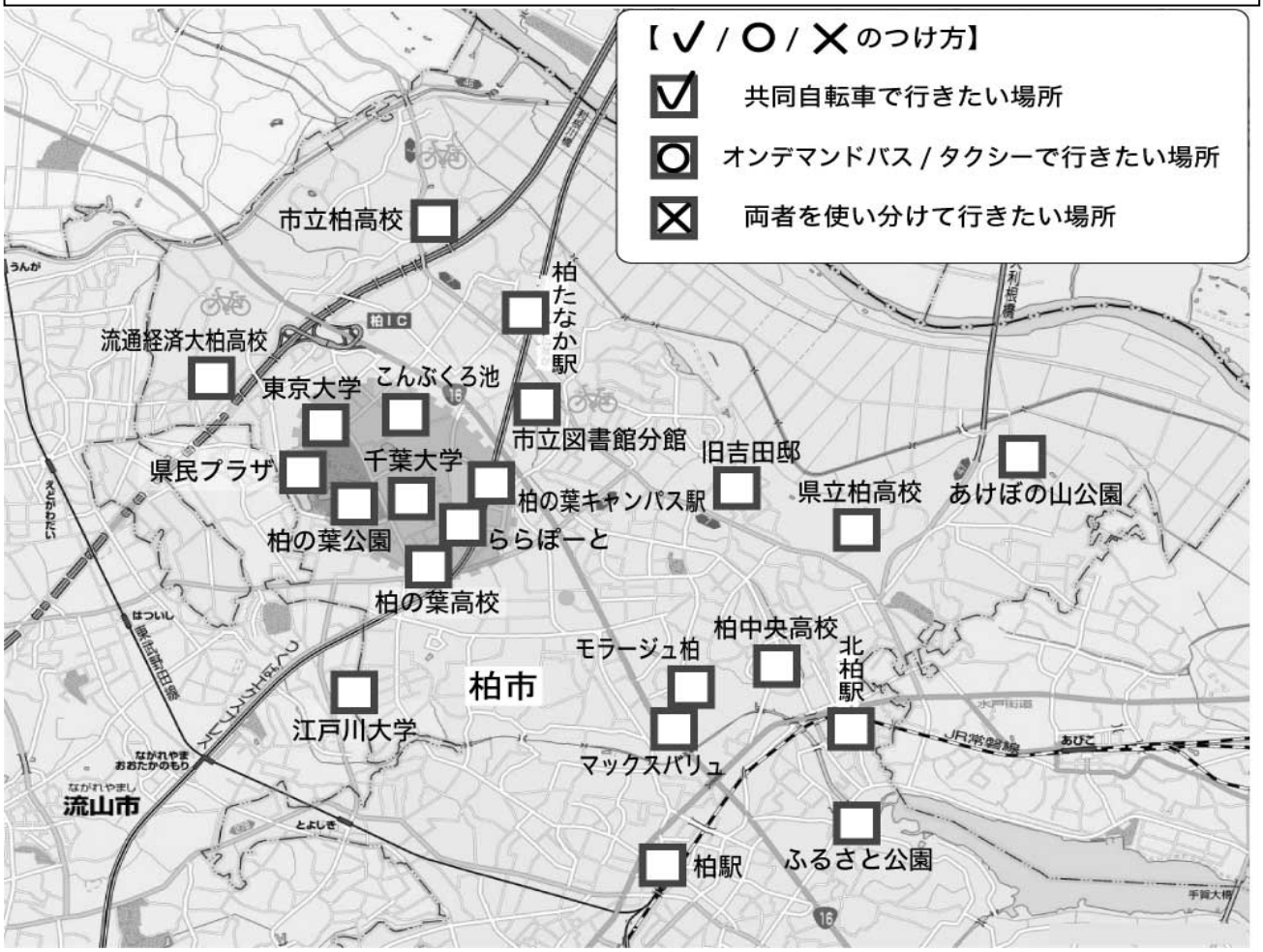
1. 是非、利用したいと思う　2. まあ、利用しようと思う　3. どちらとも言えない　4. あまり、利用しようとは思わない　5. 全く、利用しようとは思わない

※　「４」ないし「５」と回答された方は、その理由を簡単にお聞かせ下さい。

問 11：共同自転車やオンデマンドバス/タクシーを利用して、具体的にどちらへ行ってみたいと思いますか。

※　問 10 で「4」ないし「5」をお選びいただいた方）は、回答の必要はありません。

以下に、パークシティ柏の葉一番街周辺の、駅・学校・商業施設・文化施設等が挙げられています。この中で、共同自転車を利用して行きたいと思う場所に✔を、オンデマンドバス/タクシーを利用して行きたいと思う場所に○を、両者を使い分けて行きたいと思う場所に×をお願いします。



他に、共同自転車やオンデマンドバス/タクシーを使って行きたいと思う場所を、是非ご記入下さい。

（共同自転車で行きたい場所）＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿

（オンデマンドバス/タクシーで行きたい場所）＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿＿

問 12：共同自転車やオンデマンドバス/タクシーに対する以下の各評価に対し、あなたの考えに当てはまる番号それぞれ１つに○をつけてください。（「本サービス」＝「共同自転車やオンデマンドバス／タクシー」です。）

評価	とても そう思う	←	←	どちらとも いえない	→	→	全くそう 思わない
本サービスを利用して、近所でもっと多くの活動をしたい	1	2	3	4	5	6	7
現在は別の交通手段で行っている場所に、本サービスを積極的に利用して行きたい	1	2	3	4	5	6	7
現在はどの交通手段でも行っていない場所に、本サービスを利用して行きたい	1	2	3	4	5	6	7
本サービスが提供されることで、柏の葉周辺の地域的魅力が高まると思う	1	2	3	4	5	6	7
（将来転居することがあれば）本サービスがあるような地域に転居したい	1	2	3	4	5	6	7

最後に、ガソリン高騰のライフスタイルへの影響に関して、お伺いします。

問 13：昨年９月に 140 円台だったガソリン価格（レギュラー）は、今年に入り、一時 180 円台にまで上昇しました。このようなガソリン高騰が、皆様の自動車利用状況にどのように影響しているかをお伺いします。

※ **自家用車をお持ちでない方（問２で「４」をお選びいただいた方）は、以下は回答の必要はありません。**

① もし**現在もガソリン価格が 1 年前と同じ程度（レギュラーで 140 円/L）だったとしたら、現在の自動車利用状況と比較して**、あなたは自動車の利用回数を何割程度増やしていると思いますか。
「余暇/娯楽」・「買物」・「学習」・「飲食」の各活動について、交通手段として自動車を利用する回数を増やしている（と思う）かどうか、また「増やしている」場合には、**およそ何割増えるか**を**直感で**お答え下さい。

活動内容		自動車の利用回数を、現状より増やしている**と思うか** いずれかに○を。また「増やしている」場合、何割くらい回数が増えるか。
余暇/娯楽	映画，友人・親戚との面会，散歩，行楽，運動，近所でのジョギング等	1．変わっていないと思う（増やしていない）
		2．増やしていると思う　⇒（現在の利用回数より）＿＿割くらい、増える
買物	通常の買物，レンタル等 ※駅売店や自販機などでの軽微な買物は除く	1．変わっていないと思う（増やしていない）
		2．増やしていると思う　⇒（現在の利用回数より）＿＿割くらい、増える
学習 ※通学先の学校での学習は除く	図書館，英会話等の各種スクール，講演会・勉強会等	1．変わっていないと思う（増やしていない）
		2．増やしていると思う　⇒（現在の利用回数より）＿＿割くらい、増える
飲食	食堂，レストラン，喫茶店，バー，居酒屋等での飲食	1．変わっていないと思う（増やしていない）
		2．増やしていると思う　⇒（現在の利用回数より）＿＿割くらい、増える

② もし**ガソリン価格が１年前と同じ程度（レギュラーで 140 円/L）なら**、あなたは以下の表の各活動を、現在**ご自宅の近所**と**遠方（エリアは問５の図に準じます）**でそれぞれ何回程度、どの交通手段を利用して行っていると思いますか。**以下は問６と同じ回答表ですので、見比べながらご想像し、ご記入をお願い致します**。

活動内容		活動場所	A:仕事・学校のない日／仕事・学校からの帰宅後				B:仕事・学校への行き帰り時
			頻度	交通手段			頻度
				車 バイク	自転車 徒歩	公共 交通	
余暇/娯楽	映画，散歩，友人・親戚との面会，行楽，運動，近所でのジョギング等	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
買物	通常の買物，レンタル等 ※駅売店や自販機などでの軽微な買物は除く	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
学習 ※通学先の学校での学習は除く	図書館，英会話等の各種スクール，講演会・勉強会等	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度
飲食	食堂，レストラン，喫茶店，バー，居酒屋等での飲食	近所	週　月 年　回程度	回	回	回	週　月 年　回程度
		遠方	週　月 年　回程度	回	回	回	週　月 年　回程度

これでアンケートは終了です。 ご協力ありがとうございました。

国土交通省　全国都市交通特性調査

㊙ 都市調査・世帯票

この調査は、総務省の承認を得た統計調査です。
承認番号：２６２１８
承認期限：平成17年９月２日から
平成18年３月31日まで

この調査は、交通計画や、まちづくりを検討するための基礎資料を得ることを目的としています。調査票に記入された内容は、この目的以外には使用しません。

■ 記入についてのお願い
・黒の筆記用具で、世帯の代表者（世帯主）が記入して下さい。
・回答は、　　の部分（回答欄）に記入して下さい。
・回答欄に番号がある場合は、該当する番号を○で囲んで下さい。

市区町村	調査区	バッチ	世帯	人数

1　2

1 あなたの世帯のお住まいについて答えてください。

住居の種類
1. 持ち家
2. 賃貸住宅（社宅、公務員住宅、独身寮などを含む）

住居の建て方
1. 一戸建
2. 集合住宅（長屋建、テラスハウスを含む）

2 記入例を参考に、あなたの世帯の方全員について答えてください。

※いちばん左の欄の番号が、世帯の方それぞれの個人番号となりますので、個人票に個人番号を記入する場合はこの番号で答えて下さい。

個人番号	世帯主との続柄 表１から選んで番号を1つ記入して下さい	性別 番号を○で囲んで下さい	年齢 平成17年10月1日現在の年齢を記入して下さい	職業 職業を表２から選んで1つ記入して下さい	就業形態 職業をお持ちの方は表３から選んで記入して下さい	保有運転免許 保有している運転免許の番号をすべて○で囲んで下さい	自由に使える自動車 自由に使える自動車（二輪車を除く）はありますか。該当する番号を1つ○で囲んで下さい
記入例	[2]番	1. 男 (2.) 女	満 [36]歳	[3]番	[2]番	(1.) 普通または大型自動車□　3. 原動機付自転車のみ 2. 自動二輪車□　4. 持っていない	(1.) ほぼ自分専用の自動車がある 2. 家族共有の自動車がある 3. ない
1（世帯主）	1 番	1. 男 2. 女	満 [ ]歳	[ ]番	[ ]番	1. 普通または大型自動車□　3. 原動機付自転車のみ 2. 自動二輪車□　4. 持っていない	1. ほぼ自分専用の自動車がある 2. 家族共有の自動車がある 3. ない
2	[ ]番	1. 男 2. 女	満 [ ]歳	[ ]番	[ ]番	1. 普通または大型自動車□　3. 原動機付自転車のみ 2. 自動二輪車□　4. 持っていない	1. ほぼ自分専用の自動車がある 2. 家族共有の自動車がある 3. ない
3	[ ]番	1. 男 2. 女	満 [ ]歳	[ ]番	[ ]番	1. 普通または大型自動車□　3. 原動機付自転車のみ 2. 自動二輪車□　4. 持っていない	1. ほぼ自分専用の自動車がある 2. 家族共有の自動車がある 3. ない
4	[ ]番	1. 男 2. 女	満 [ ]歳	[ ]番	[ ]番	1. 普通または大型自動車□　3. 原動機付自転車のみ 2. 自動二輪車□　4. 持っていない	1. ほぼ自分専用の自動車がある 2. 家族共有の自動車がある 3. ない
5	[ ]番	1. 男 2. 女	満 [ ]歳	[ ]番	[ ]番	1. 普通または大型自動車□　3. 原動機付自転車のみ 2. 自動二輪車□　4. 持っていない	1. ほぼ自分専用の自動車がある 2. 家族共有の自動車がある 3. ない
6	[ ]番	1. 男 2. 女	満 [ ]歳	[ ]番	[ ]番	1. 普通または大型自動車□　3. 原動機付自転車のみ 2. 自動二輪車□　4. 持っていない	1. ほぼ自分専用の自動車がある 2. 家族共有の自動車がある 3. ない

表１　世帯主との続柄

1. 本人□
2. 妻・夫□
3. 子□
4. 孫□
5. 兄弟・姉妹□
6. 父・母□
7. 祖父・祖母
8. いとこ
9. おじ・おば
10. おい・めい
11. その他

表２　職業の分類

●職業をお持ちの方（パート・アルバイトを含む。ただし学生は除く）
1. 農林漁業作業者□
2. 生産工程・労務作業者□
3. 販売従事者□
4. サービス職業従事者□
5. 運輸・通信従事者□
6. 保安職業従事者
7. 事務従事者
8. 専門的・技術的職業従事者
9. 管理的職業従事者
10. その他職業

●職業をお持ちでない方
11. 中学生以下（生徒･児童･園児など）
12. 高校以上の学生
13. 主婦･主夫（職業従事者を除く）
14. 無職
15. その他

表３　就業形態

1. 自営業主・家族従業者
2. 正規の職員・従業員、派遣社員、契約社員　等
3. パート・アルバイト
4. 会社などの役員
5. その他

3 世帯で所有、または通常使用している自動車や自転車などの台数を答えて下さい。

※会社の車で、通常、家に持ち帰って使用している車を含みます。

自動車	軽乗用車 [ ]台	乗用車 [ ]台	軽貨物車 [ ]台	貨物自動車 [ ]台
二輪車	自動二輪車（50ccを超える）[ ]台	原動機付自転車（50cc以下）[ ]台	自転車 [ ]台	

国土交通省　全国都市交通特性調査

秘 都市調査・個人票 平日

この調査は、総務省の承認を得た統計調査です。
承認番号：２６２１９
承認期限：平成17年９月２日から平成18年３月31日まで

この調査は、交通計画や、まちづくりを検討するための基礎資料を得ることを目的としています。調査票に記入された内容は、この目的以外には使用しません。

■ 記入についてのお願い
・黒の筆記用具で記入して下さい。
・回答は、　　の部分（回答欄）に記入して下さい。
・回答欄に番号がある場合は、該当する番号を○で囲んで下さい。

市区町村	調査区	バッチ	世帯	トリップ

1	2

トリップ	1	2

1 世帯票を回答した後に記入して下さい。
世帯票でのあなたの個人番号を答えて下さい。 [　　] 番

5歳以上（平成17年10月1日現在）の方一人ひとりが、それぞれの調査票に記入して下さい。

1日のあなたの行動について、**2** 以降の質問に番号順に答えて下さい。調査日は、平成 17 年　　月　　日（　　曜日）午前３時から翌日の午前３時までです。
場所が自宅と同じ場合には「1」に○をつけ、それ以外の場合は、具体的な所在地または目標物名（建物の名称、付近の有名な建物、停留所名など）を記入して下さい。

続きがある場合には、調査員あるいは調査実施本部に連絡して下さい。

2 1日のはじめにいた場所
1. 自宅
2. 自宅以外　※所在地または目標物を記入
【所在地】
都道府県　市郡
区町村　町
丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など
[　　]

4 １番目に行った場所
1. 自宅
2. 自宅以外　※所在地または目標物を記入
【所在地】
都道府県　市郡
区町村　町
丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など
[　　]

6 ２番目に行った場所
1. 自宅
2. 自宅以外　※所在地または目標物を記入
【所在地】
都道府県　市郡
区町村　町
丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など
[　　]

8 ３番目に行った場所
1. 自宅
2. 自宅以外　※所在地または目標物を記入
【所在地】
都道府県　市郡
区町村　町
丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など
[　　]

10 ４番目に行った場所
1. 自宅
2. 自宅以外　※所在地または目標物を記入
【所在地】
都道府県　市郡
区町村　町
丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など
[　　]

12 ５番目に行った場所
1. 自宅
2. 自宅以外　※所在地または目標物を記入
【所在地】
都道府県　市郡
区町村　町
丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など
[　　]

14 ６番目に行った場所
1. 自宅
2. 自宅以外　※所在地または目標物を記入
【所在地】
都道府県　市郡
区町村　町
丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など
[　　]

	3	**5**	**7**	**9**	**11**	**13**
出発時刻と到着時刻は	出発時刻は 1. 午前 2. 午後 ・ 時 ・ 分 到着時刻は 1. 午前 2. 午後 ・ 時 ・ 分	出発時刻は 1. 午前 2. 午後 ・ 時 ・ 分 到着時刻は 1. 午前 2. 午後 ・ 時 ・ 分	出発時刻は 1. 午前 2. 午後 ・ 時 ・ 分 到着時刻は 1. 午前 2. 午後 ・ 時 ・ 分	出発時刻は 1. 午前 2. 午後 ・ 時 ・ 分 到着時刻は 1. 午前 2. 午後 ・ 時 ・ 分	出発時刻は 1. 午前 2. 午後 ・ 時 ・ 分 到着時刻は 1. 午前 2. 午後 ・ 時 ・ 分	出発時刻は 1. 午前 2. 午後 ・ 時 ・ 分 到着時刻は 1. 午前 2. 午後 ・ 時 ・ 分
そこに行った目的は	表１から選択 [　　] 番	表１から選択 [　　] 番	表１から選択 [　　] 番	表１から選択 [　　] 番	表１から選択 [　　] 番	表１から選択 [　　] 番
利用した交通手段の種類と所要時間は（※分単位で記入して下さい）	表２から選択 はじめに ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した	表２から選択 はじめに ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した	表２から選択 はじめに ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した	表２から選択 はじめに ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した	表２から選択 はじめに ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した	表２から選択 はじめに ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した 次に ・ を ・ 分 利用した
そこまでの距離は	およそ [　　] km	およそ [　　] km	およそ [　　] km	およそ [　　] km	およそ [　　] km	およそ [　　] km
自動車を利用した方のみ回答（表２で６～９を選んだ方）：誰が運転しましたか	世帯票の個人番号 [　　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　　] 番 ※世帯以外の方の運転は「0」を記入
運転した方のみ回答：何人乗車しましたか	家族の方はあなたを含めて [　　] 人 家族以外の方は [　　] 人	家族の方はあなたを含めて [　　] 人 家族以外の方は [　　] 人	家族の方はあなたを含めて [　　] 人 家族以外の方は [　　] 人	家族の方はあなたを含めて [　　] 人 家族以外の方は [　　] 人	家族の方はあなたを含めて [　　] 人 家族以外の方は [　　] 人	家族の方はあなたを含めて [　　] 人 家族以外の方は [　　] 人
運転した方のみ回答：どこに駐車しましたか	どこに駐車しましたか 表３から選択 [　　] 番	どこに駐車しましたか 表３から選択 [　　] 番	どこに駐車しましたか 表３から選択 [　　] 番	どこに駐車しましたか 表３から選択 [　　] 番	どこに駐車しましたか 表３から選択 [　　] 番	どこに駐車しましたか 表３から選択 [　　] 番

うら面の 休日 個人票にもご記入下さい

表１ 目　的

1. 勤務先へ（帰社を含む）□
2. 通学先へ（帰校を含む）□
3. 自宅へ
【私用目的】□
4. 買物へ□
5. 食事・社交・娯楽へ（日常生活圏内）□
6. 観光・行楽・レジャーへ（日常生活圏をこえる）
7. その他の私用へ（通院・塾・習い事など）□
8. 送迎
【業務目的】
9. 販売・配達・仕入・購入先へ
10. 打合せ・会議・集金・往診へ
11. 作業・修理へ
12. 農林漁業作業へ
13. その他の業務へ

表２ 交通手段

1. 徒歩□
2. 自転車□
3. 原動機付自転車（50cc以下）□
4. 自動二輪車（50cc超）□
5. タクシー・ハイヤー□
6. 乗用車□
7. 軽乗用車□
8. 貨物自動車（ライトバンを含む）□
9. 軽貨物車□
10. 自家用バス・貸切バス（送迎バスを含む）□
11. 路線バス（高速バスを含む）□
12. モノレール・新交通
13. 路面電車
14. 鉄道・地下鉄
15. 船舶
16. 航空機
17. その他

表３ 駐車場所

●道路上
1. 有料　パーキングメーター／パーキングチケット　など
2. 無料

●道路外
有料
3. 月極
4. 時間貸し
5. 店舗等の有料駐車場
無料
6. 自宅車庫
7. 勤務先・訪問先の敷地内
8. 店舗等の駐車場（買物割引での無料を含む）
9. 駅前広場
10. その他の空き地など

●駐車せず
11. 駐車しなかった

秘 都市調査・個人票 休日

この調査は、交通計画や、まちづくりを検討するための基礎資料を得ることを目的としています。調査票に記入された内容は、この目的以外には使用しません。

■ 記入についてのお願い
- 黒の筆記用具で記入して下さい。
- 回答は、　　の部分（回答欄）に記入して下さい。
- 回答欄に番号がある場合は、該当する番号を〇で囲んで下さい。

トリップ

1 2 / トリップ 1 2

1 世帯票を回答した後に記入して下さい。
世帯票でのあなたの個人番号を答えて下さい。 [　　] 番

5歳以上（平成17年10月1日現在）の方一人ひとりが、それぞれの調査票に記入して下さい。

1日のあなたの行動について、**2** 以降の質問に番号順に答えて下さい。**調査日は、平成17年　　月　　日（日曜日）午前3時から翌日の午前3時までです。**
場所が自宅と同じ場合には「1」に〇をつけ、それ以外の場合は、具体的な所在地または目標物名（建物の名称、付近の有名な建物、停留所名など）を記入して下さい。

続きがある場合は、調査員あるいは調査実施本部に連絡して下さい。

2 1日のはじめにいた場所
1. 自宅
2. 自宅以外 ※所在地または目標物を記入
【所在地】 都道府県　市郡　区町村　町　丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など [　　]

4 1番目に行った場所
1. 自宅
2. 自宅以外 ※所在地または目標物を記入
【所在地】 都道府県　市郡　区町村　町　丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など [　　]

6 2番目に行った場所
1. 自宅
2. 自宅以外 ※所在地または目標物を記入
【所在地】 都道府県　市郡　区町村　町　丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など [　　]

8 3番目に行った場所
1. 自宅
2. 自宅以外 ※所在地または目標物を記入
【所在地】 都道府県　市郡　区町村　町　丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など [　　]

10 4番目に行った場所
1. 自宅
2. 自宅以外 ※所在地または目標物を記入
【所在地】 都道府県　市郡　区町村　町　丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など [　　]

12 5番目に行った場所
1. 自宅
2. 自宅以外 ※所在地または目標物を記入
【所在地】 都道府県　市郡　区町村　町　丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など [　　]

14 6番目に行った場所
1. 自宅
2. 自宅以外 ※所在地または目標物を記入
【所在地】 都道府県　市郡　区町村　町　丁目　大字　字
【目標物】※建物の名称、付近の有名な建物、停留所名など [　　]

	3	5	7	9	11	13
出発時刻と到着時刻は	出発時刻は 1. 午前 2. 午後 時 分 到着時刻は 1. 午前 2. 午後 時 分	出発時刻は 1. 午前 2. 午後 時 分 到着時刻は 1. 午前 2. 午後 時 分	出発時刻は 1. 午前 2. 午後 時 分 到着時刻は 1. 午前 2. 午後 時 分	出発時刻は 1. 午前 2. 午後 時 分 到着時刻は 1. 午前 2. 午後 時 分	出発時刻は 1. 午前 2. 午後 時 分 到着時刻は 1. 午前 2. 午後 時 分	出発時刻は 1. 午前 2. 午後 時 分 到着時刻は 1. 午前 2. 午後 時 分
そこに行った目的は	表1 から選択 [　] 番	表1 から選択 [　] 番	表1 から選択 [　] 番	表1 から選択 [　] 番	表1 から選択 [　] 番	表1 から選択 [　] 番
利用した交通手段の種類と所要時間は（※分単位で記入して下さい）	表2 から選択 はじめに [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した	表2 から選択 はじめに [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した	表2 から選択 はじめに [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した	表2 から選択 はじめに [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した	表2 から選択 はじめに [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した	表2 から選択 はじめに [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した 次に [　] を [　] 分 利用した
そこまでの距離は	およそ [　] km	およそ [　] km	およそ [　] km	およそ [　] km	およそ [　] km	およそ [　] km
自動車を利用した方のみ回答（表2で6～9を選んだ方） 誰が運転しましたか	世帯票の個人番号 [　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　] 番 ※世帯以外の方の運転は「0」を記入	世帯票の個人番号 [　] 番 ※世帯以外の方の運転は「0」を記入
運転した方のみ回答 何人乗車しましたか	家族の方はあなたを含めて [　] 人 家族以外の方は [　] 人	家族の方はあなたを含めて [　] 人 家族以外の方は [　] 人	家族の方はあなたを含めて [　] 人 家族以外の方は [　] 人	家族の方はあなたを含めて [　] 人 家族以外の方は [　] 人	家族の方はあなたを含めて [　] 人 家族以外の方は [　] 人	家族の方はあなたを含めて [　] 人 家族以外の方は [　] 人
運転した方のみ回答 どこに駐車しましたか	どこに駐車しましたか 表3 から選択 [　] 番	どこに駐車しましたか 表3 から選択 [　] 番	どこに駐車しましたか 表3 から選択 [　] 番	どこに駐車しましたか 表3 から選択 [　] 番	どこに駐車しましたか 表3 から選択 [　] 番	どこに駐車しましたか 表3 から選択 [　] 番

ご協力ありがとうございました

表1 目　的

1. 勤務先へ（帰社を含む）□
2. 通学先へ（帰校を含む）□
3. 自宅へ
【私用目的】□
4. 買物へ□
5. 食事・社交・娯楽へ（日常生活圏内）□
6. 観光・行楽・レジャーへ（日常生活圏をこえる）□
7. その他の私用へ（通院・塾・習い事など）□
8. 送迎□
【業務目的】
9. 販売・配達・仕入・購入先へ
10. 打合せ・会議・集金・往診へ
11. 作業・修理へ
12. 農林漁業作業へ
13. その他の業務へ

表2 交通手段

1. 徒歩□
2. 自転車□
3. 原動機付自転車（50cc以下）□
4. 自動二輪車（50cc超）□
5. タクシー・ハイヤー□
6. 乗用車□
7. 軽乗用車□
8. 貨物自動車（ライトバンを含む）□
9. 軽貨物車□
10. 自家用バス・貸切バス（送迎バスを含む）□
11. 路線バス（高速バスを含む）□
12. モノレール・新交通
13. 路面電車
14. 鉄道・地下鉄
15. 船舶
16. 航空機
17. その他

表3 駐車場所

●道路上
1. 有料 [パーキングメーター / パーキングチケット] など
2. 無料

●道路外
有料
3. 月極
4. 時間貸し
5. 店舗等の有料駐車場
無料
6. 自宅車庫
7. 勤務先・訪問先の敷地内
8. 店舗等の駐車場（買物割引での無料を含む）
9. 駅前広場
10. その他の空き地など

●駐車せず
11. 駐車しなかった

都市交通に関する意識調査

■ 記入についてのお願い
・黒の筆記用具で記入して下さい。
・回答は、　　の部分（回答欄）に記入して下さい。
・回答欄に番号がある場合は、該当する番号を〇で囲んで下さい。

市区町村	調査区	バッチ	世帯

問1 世帯票でのあなたの個人番号を記入して下さい。[　　] 番

18歳以上（平成17年10月1日現在）の方一人ひとりが記入して下さい。

問2 交通機関の利用状況についてお聞きします。

(1) 以下の交通機関をどのくらい利用していますか。

【記入例】月に３日程度の場合
1. 年に ②. 月に 3. 週に 3 日程度

①鉄道は
1. 年に 2. 月に 3. 週に　　日程度

②路線バスは
1. 年に 2. 月に 3. 週に　　日程度

③自動車は
1. 年に 2. 月に 3. 週に　　日程度

④自転車は
1. 年に 2. 月に 3. 週に　　日程度

⑤徒歩だけでの外出は
1. 年に 2. 月に 3. 週に　　日程度

(2) 通勤・通学されている方にお聞きします。
通勤・通学時に利用している交通手段は何ですか。主な交通機関１つに〇をして下さい。

1. 鉄道　2. 路線バス　3. 自動車　4. 自転車　5. 徒歩　6. その他

問3 転居の経験についてお聞きします。

(1) 転居の経験はありますか。

1. ある ➡ 現在の場所にいつからお住まいですか。　昭和・平成　　年　　月から
2. ない ➡ 問4 へお進み下さい

(2) 現在の居住地の前にお住まいの場所はどこですか。

都道府県	市郡	区町村	町丁目

(3) (2)の場所では、以下の交通機関をどのくらい利用していましたか。

【記入例】月に３日程度の場合
1. 年に ②. 月に 3. 週に 3 日程度

①鉄道は
1. 年に 2. 月に 3. 週に　　日程度

②路線バスは
1. 年に 2. 月に 3. 週に　　日程度

③自動車は
1. 年に 2. 月に 3. 週に　　日程度

④自転車は
1. 年に 2. 月に 3. 週に　　日程度

⑤徒歩だけでの外出は
1. 年に 2. 月に 3. 週に　　日程度

(4) (2)の場所での住居の種類、建て方は何ですか。

①住居の種類は
1. 持ち家　2. 賃貸住宅（社宅、公務員住宅、独身寮などを含む）

②建て方は
1. 一戸建て　2. 集合住宅（長屋建、テラスハウスなどを含む）

(5) 転居する際に、複数の転居先を比べて、お選びになりましたか。あるいは、社宅への入居、家族の家への同居、相続した家への居住などで、転居先は決まっていましたか。

1. 複数の転居先を比べて選んだ ➡ (6)へお進み下さい
2. 転居先は決まっていた ➡ 問4 へお進み下さい

(6) 現在のお住まいを選ぶ際に、以下の①～⑥をどの程度考慮しましたか。

	全く考慮していない	あまり考慮していない	どちらでもない	少し考慮した	よく考慮した
①中心市街地への行きやすさ	1.	2.	3.	4.	5.
②大規模ショッピングセンターへの行きやすさ	1.	2.	3.	4.	5.
③駐車場の確保のしやすさ	1.	2.	3.	4.	5.
④鉄道・バスの利用しやすさ	1.	2.	3.	4.	5.
⑤徒歩や自転車の移動範囲で日常生活の用事が済む	1.	2.	3.	4.	5.
⑥自動車による移動のしやすさ	1.	2.	3.	4.	5.

問4 将来の転居についてお聞きします。

(1) もし、次に転居するならば、以下の①～⑥をどの程度考慮すると思いますか

	全く考慮しない	あまり考慮しない	どちらでもない	少し考慮する	よく考慮する
①中心市街地への行きやすさ	1.	2.	3.	4.	5.
②大規模ショッピングセンターへの行きやすさ	1.	2.	3.	4.	5.
③駐車場の確保のしやすさ	1.	2.	3.	4.	5.
④鉄道・バスの利用しやすさ	1.	2.	3.	4.	5.
⑤徒歩や自転車の移動範囲で日常生活の用事が済む	1.	2.	3.	4.	5.
⑥自動車による移動のしやすさ	1.	2.	3.	4.	5.

(2) 現在のお住まいから転居する予定はありますか。

1. 転居する予定がある　2. 転居を考えたことはあるが、具体的なことまでは考えていない
3. 転居を考えたことはない

問5 中心市街地・郊外ショッピングセンターに関する意識についてお聞きします。

※中心市街地とは、古くから商店が集積し、市を代表する地域のことです。

(1) あなたがお住まいの市の中心市街地はどこですか。

（例）〇〇商店街、〇〇デパート周辺

(2) よく出かける郊外ショッピングセンターはどこですか。

（例）〇〇ショッピングセンター　△△店、〇〇プラザ

(3) (1)の中心市街地、(2)の郊外ショッピングセンターに出かける時について以下の問いにお答え下さい。

	中心市街地	郊外ショッピングセンター
①一緒に出かける人	1. 家族　2. 友人　3. あなた１人	1. 家族　2. 友人　3. あなた１人
②利用交通機関（多いもの１つに〇）	1. 鉄道　2. バス　3. タクシー　4. 自動車　4. バイク　5. 自転車　7.徒歩	1. 鉄道　2. バス　3. タクシー　4. 自動車　4. バイク　5. 自転車　7.徒歩
③ ②の交通機関での所要時間	約　　分	約　　分

(4) 中心市街地、郊外ショッピングセンターに買物で出かける頻度はどの程度ですか。

①中心市街地
1. 月に 2. 週に　　回程度

②郊外ショッピングセンター
1. 月に 2. 週に　　回程度

※郊外ショッピングセンターの頻度は(2)の施設だけでなく他の施設の分も含めた合計を記入して下さい

(5) 買物以外の目的で中心市街地に出かけることはありますか。また、その目的は何ですか。
（「買物のついでに出かける目的」「買物とは別に出かける目的」を含めてお答え下さい。）

1. ある ➡ 買物以外で出かける目的は（主なもの２つに〇）
2. ほとんどない

1. 通勤　2. 通学　3. 業務　4. 通院　5. 娯楽　6. 食事　7. その他

(6) 以下の①～⑩のイメージは、中心市街地と郊外ショッピングセンターのどちらに当てはまると思いますか。

	中心市街地	どちらかというと中心市街地	どちらでもない	どちらかというと郊外	郊外ショッピングセンター
①公共交通（鉄道・バス）で行きやすい	1.	2.	3.	4.	5.
②自動車で行きやすい	1.	2.	3.	4.	5.
③歩いて楽しい	1.	2.	3.	4.	5.
④歴史・文化的蓄積がある	1.	2.	3.	4.	5.
⑤用事が一度に済む	1.	2.	3.	4.	5.
⑥飲食店や娯楽施設が多い	1.	2.	3.	4.	5.
⑦値段が安い	1.	2.	3.	4.	5.
⑧高級品や専門的品物が買える	1.	2.	3.	4.	5.
⑨イベントや娯楽がある	1.	2.	3.	4.	5.
⑩店の人とのコミュニケーションが楽しい	1.	2.	3.	4.	5.

問6　中心市街地の活性化についてお聞きします。

(1) 最近、中心市街地の活力が低下している都市が多く、活性化を図るべきであるという意見があります。
あなたがお住まいの市における中心市街地の活性化についてどのように思いますか。

1. 中心市街地を活性化させるべきである　2. 中心市街地を活性化させるべきとは思わない

(2) あなたがお住まいの市において、中心市街地を活性化させるために、どのようなことが重要と思いますか。
（あなたのお考えに近いもの１つに〇）

1. 道路の拡幅・整備や駐車場整備を行って、自動車で中心市街地に行きやすくする
2. 歩行空間の整備を行って、中心市街地を歩きやすくする
3. 鉄道・バスなどの公共交通機関の利便性を高め、公共交通で中心市街地に行きやすくする
4. 中心市街地活性化のための対策は特に必要ない

問7　通信販売や宅配サービス、インターネットを利用した買物（ネットショッピング）についてお聞きします。

(1) 通信販売や宅配サービスで品物を購入したことがありますか。

①テレビショッピングやカタログショッピング
1. ある ➡ どの程度利用していますか。
1. 年に 2. 月に ＿＿ 回程度
2. ない

②スーパー・生協等の宅配サービス
1. ある ➡ どの程度利用していますか
1. 年に 2. 月に ＿＿ 回程度
2. ない

(2) ネットショッピングの利用についてお聞きします。

①ネットショッピングのサイトを閲覧したことがありますか。
1. ある ➡ どの程度閲覧していますか。
1. 月に 2. 週に ＿＿ 時間程度
2. ない

②ネットショッピングで品物を購入したことはありますか。
1. ある ➡ どの程度利用していますか。
1. 年に 2. 月に ＿＿ 回程度
2. ない

(3) 通信販売や宅配サービス、ネットショッピングでの購入や閲覧により、日常の買物はどのように変化しましたか。

1. このようなサービスを利用しても、日常の買物に出かける回数は変わらない
2. このようなサービスを利用することにより、日常の買物に出かける回数は少なくなった

問8　日常の外出についてお聞きします。

(1) 日常の生活で交通が不便などの理由から外出を控えていることはありますか。

1. 控えている ➡ 外出を控えている理由は何ですか　（当てはまるもの２つ以内に〇）
1. 公共交通の乗降時に段差が多い　2. 街なかの歩道に段差が多い
3. 目的地まで直接行ける公共交通機関がない　4. 公共交通機関の運行本数が少ない
5. 家族の都合に合わせなければならない　6. その他

2. 控えていない

(2) 外出するときに次のようなものを利用しますか。

1. 杖（つえ）　2. 手押しカート　3. シニアカー　4. 車いす　5. 特に利用しない

(3) 徒歩や(2)の手段で休まずに移動できる距離はどの程度ですか。

1. 100m程度まで　2. 300m程度まで　3. 500m程度まで　4. 1km程度まで　5. 1.5km程度まで
6. 1.5km以上 ➡【具体的には ＿＿ km程度】

(4) 自転車で移動してもよいと思う距離はどの程度ですか。

1. 自転車は利用しない　2. 500m程度まで　3. 1km程度まで　4. 2km程度まで　5. 3km程度まで
6. 3km以上 ➡【具体的には ＿＿ km程度】

問9　自動車の運転免許の保有と自動車運転の状況についてお聞きします。

現在自動車運転免許をお持ちですか。

1. 持っていて運転している ➡ 問9-1へ
2. 持っているがほとんど運転しない ➡ 問9-2へ
3. 現在は持っていないが過去に持っていた ➡ 問9-3へ
4. 一度も持ったことがない ➡ これで終了です

問9-1　自動車運転免許をお持ちで運転している方にうかがいます。

(1) 今後も自動車の運転を継続しますか。

1. 運転を継続しない ➡ (2)にお進み下さい
2. どちらともいえない ➡ (3)にお進み下さい
3. 運転を継続する ➡ (3)にお進み下さい

(2) (1)で「1. 運転を継続しない」とお答えの方にうかがいます。
自動車の運転を継続しない理由は何ですか。（当てはまるもの２つ以内に〇）

1. 自動車を利用する必要がなくなったから　2. 公共交通が便利だから
3. 自動車の維持費用が高いから　4. 自分の運転に自信がなくなったから

(3) 次回の更新時期に運転免許を更新しますか。

1. 更新する　2. どちらともいえない　3. 更新しない

問9-2　自動車の運転免許を持っているが、ほとんど運転していない方にうかがいます。

(1) 運転しなくなったのはいつ頃ですか。　約［＿＿］年前　（1年未満の方は「0年前」とご記入下さい。）

(2) 運転しなくなった理由は何ですか。（当てはまるもの２つ以内に〇）

1. 自動車を利用する必要がなくなったから　2. 公共交通が便利だから
3. 自動車の維持費用が高いから　4. 自分の運転に自信がなくなったから

(3) 運転しなくなってから移動はどのように変化しましたか。（当てはまるもの２つ以内に〇）

1. 鉄道やバスなどの公共交通機関を利用している　2. 徒歩や自転車で出かけられる範囲で移動している
3. 家族に自動車で送迎してもらうようになった　4. 外出することが減った

(4) 次回の更新時期に運転免許を更新しますか。

1. 更新する　2. どちらともいえない　3. 更新しない

問9-3　過去に自動車運転免許を持っていて、現在持っていない方にうかがいます。

(1) 免許を持たなくなったのはいつ頃ですか。　約［＿＿］年前　（1年未満の方は「0年前」とご記入下さい。）

(2) 免許を持たなくなった理由は何ですか。（当てはまるもの２つ以内に〇）

1. 自動車を利用する必要がなくなったから　2. 公共交通が便利だから
3. 自動車の維持費用が高いから　4. 自分の運転に自信がなくなったから
5. 免許取り消しになったから

(3) 免許を持たなくなってから移動はどのように変化しましたか。（当てはまるもの２つ以内に〇）

1. 鉄道やバスなどの公共交通機関を利用している　2. 徒歩や自転車で出かけられる範囲で移動している
3. 家族に自動車で送迎してもらうようになった　4. 外出することが減った

ご協力ありがとうございました

アンケートページにアクセスいただきまして、ありがとうございます。
今回のアンケートは、「あなた自身に関するアンケート」です。

【モニターの皆様へのお願い】

本アンケートは一般に公開していない情報が含まれる場合がございます。
アンケート内で知り得た、いかなる情報についても、決して第三者に口外なさらぬようお願いします。

「第三者への口外」に含まれる例

・口頭、電話、メール等で友人・知人に情報共有すること
・掲示板やブログに書き込むことで不特定多数に情報共有すること
・その他いかなる手段でも情報が漏れてしまうことに寄与する行為

ご確認のお願い

本アンケートは、「広島市在住」の方にお送りしております。

上記にあてはまらない方は、恐れ入りますが回答をご遠慮くださいます様お願いいたします。

【注意事項】
・当社は会員の個人情報を、個人情報保護方針に基づいて取り扱います。
・複数のアンケート画面を同時に開きますと、正常に回答できず、ポイント付与の対象になりません。
同時に複数のアンケートにご回答なさらないようにご注意ください。
・当社のアンケートへの回答は、Internet Explorer 7、8を推奨環境とさせていただいております。

「同意し、アンケート開始」ボタンをクリックすると、アンケート画面が別ウィンドウで表示されます。
上記注意事項にご同意いただけない場合は、下の「閉じる」ボタンをクリックしてください。

同意し、アンケート開始

閉じる

改ページ

Q1 【必須】 あなたの【現在のお住まい】の住所を町丁目まで
（〇丁目という表示で無い場合は「字」または「町名」まで）お答えください。

【回答例1】広島県広島市中区大手町6丁目1-1の場合⇒広島県広島市中区大手町6丁目　とお答えください。
【回答例2】広島県広島市安佐南区沼田町大字伴9,999の場合
⇒広島県広島市安佐南区沼田町大字伴　とお答えください。

広島県広島市 （制限なし）

次へ

改ページ

Q2 【必須】 同居しているご家族の人数をお答えください。

※ご自身を含めた人数でお答えください。

○ 1人
○ 2人

○ 3人
○ 4人
○ 5人
○ 6人
○ 7人
○ 8人以上

次へ

改ページ

分岐条件
分岐条件式　　:(Q2 ornot 1)

Q3
【必須】
同居しているご家族の中で、各選択肢に当てはまる年齢層をすべてお選びください。
(いくつでも)

□ 未就学児
□ 小学生
□ 中学生
□ 高校生
□ 18～29歳※高校生は含まない
□ 30～49歳
□ 50～64歳
□ 65歳以上(自動車を自分で運転できる)
□ 65歳以上(自動車を自分で運転できない)

次へ

改ページ

Q4
【必須】
あなたの世帯年収はおおよそいくらですか。以下選択肢よりお選びください。

○ 400万円以下
○ 401万円～600万円
○ 601万円～800万円
○ 801万円～1,000万円
○ 1,001万円～1,200万円
○ 1,201万円以上
○ わからない/答えたくない

次へ

改ページ

Q5
【必須】
あなたの世帯で【自転車】を何台持っているかをお答えください。

○ 持っていない
○ 1台
○ 2台
○ 3台
○ 4台
○ 5台
○ 6台
○ 7台
○ 8台以上

次へ

改ページ

Q6 自宅から最寄駅までの移動で最もよく使う手段をお答えください。
【必須】

- ○ 1. 徒歩
- ○ 2. 自動車
- ○ 3. バス
- ○ 4. 自転車
- ○ 5. バイク・オートバイなど動力付き二輪車
- ○ 6. その他
- ○ 7. 最寄駅がない／最寄駅がわからない

次へ

改ページ

分岐条件
分岐条件式 :(Q6 ornot 7)

Q7 自宅から最寄駅まで、最もよく使う手段での所要時間をお答えください。
【必須】 (半角数字でご記入ください)

[ ] 分【必須】(数字のみ)

次へ

改ページ

分岐条件
分岐条件式 :(Q6 ornot 7)

Q8 あなたのお住まいの最寄駅について、路線名＋駅名をお答えください。
【必須】
※路面電車の電停、アストラムラインの駅を含みます。バス停は含みません。

路線名: [ ] 【必須】(制限なし) 駅名: [ ] 【必須】(制限なし)

次へ

改ページ

Q9 ご自宅からお出かけになる際に、ご自宅付近を通るバスを利用することがあるかどうかをお答えください。
【必須】

- ○ 1. 利用することがある(ごく稀に利用する場合も含む)
- ○ 2. 利用することはまったくない

次へ

改ページ

分岐条件
分岐条件式 :(Q9 or 1)

Q10 【必須】 ご自宅の最寄りのバス停まで、徒歩で何分かかるかお答えください。
（半角数字でご記入ください）

[ ] 分【必須】(数字のみ)

次へ

改ページ

Q11 【必須】 現在のお住まいの住宅タイプについて、当てはまるものをお選びください。

- ○ 1. 賃貸集合住宅
- ○ 2. 賃貸戸建住宅
- ○ 3. 分譲集合住宅
- ○ 4. 分譲戸建住宅
- ○ 5. 社宅・寮
- ○ 6. その他

次へ

改ページ

Q12 【必須】 あなたの現在のご職業をお答えください。

- ○ 1. 会社員
- ○ 2. 公務員
- ○ 3. 派遣・契約社員
- ○ 4. 自営業
- ○ 5. 自由業／フリーランス
- ○ 6. その他有職業
- ○ 7. 学生
- ○ 8. アルバイト
- ○ 9. 専業主婦・主夫
- ○ 10. 無職

次へ

改ページ

分岐条件

分岐条件式 :(Q12 or 1, 2, 3, 4, 5, 6, 7, 8)

Q13 【必須】 あなたの【通勤先・通学先など】の住所を町丁目までお答えください。

【回答例1】広島県広島市中区大手町6丁目1-1の場合⇒広島県広島市中区大手町6丁目 とお答えください。
【回答例2】広島県広島市安佐南区沼田町大字伴9,999の場合
⇒広島県広島市安佐南区沼田町大字伴 とお答えください。

※特定の通勤通学先などが無い場合は「なし」とお答えください。

[ ] （制限なし）

次へ

改ページ

Q14 【必須】 あなたの同居家族の中で、日常的に運転をしている方の人数をお答えください。

※ご自身も含めた人数でお答えください。

- ○ 0人
- ○ 1人
- ○ 2人
- ○ 3人
- ○ 4人
- ○ 5人
- ○ 6人
- ○ 7人
- ○ 8人以上

次へ

改ページ

■以下の設問では、交通に関する習慣、交通行動やあなたのライフスタイルについてお伺いします。

Q15 【必須】 以下の設問に直感でお答えください。
以下の行動を行う際、どの交通手段を利用しますか。
（あまり行かない場所についても、「もし行くことになったら」という想定でお答えください）
（矢印方向にそれぞれひとつだけ）

	1. 自動車	2. 電車・バスなどの公共交通	3. 自転車	4. 徒歩	5. バイク	6. その他
1.スーパーに行く時	○	○	○	○	○	○
2.広島市外に住んでいる友達に訪問する時	○	○	○	○	○	○
3.コンビニへ行く時	○	○	○	○	○	○
4.海へ行く時	○	○	○	○	○	○
5.スキーリゾートに行く時	○	○	○	○	○	○
6.公園に行く時	○	○	○	○	○	○
7.温泉に行く時	○	○	○	○	○	○
8.映画を見に行く時	○	○	○	○	○	○
9.レストランに夕飯を食べに行く時	○	○	○	○	○	○
10.洋服を買いに行く時	○	○	○	○	○	○

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Q16 【必須】 以下の質問、自動車について、あなたはどのように思いますか。それぞれお答えください。
（矢印方向にそれぞれひとつだけ）

	1. そう思う	2. どちらかと言えば	3. どちらとも言えな	4. どちらかと言えば	5. そう思わない

		そう思う	い	そう思わない	
1.車を運転するときに自由を感じる	○	○	○	○	○
2.車を運転することが好き	○	○	○	○	○
3.環境に配慮するには、車の運転をやめるより、電気自動車などに変えた方がいいと思う	○	○	○	○	○
4.自分で自由に車を使えると、車を使わない時よりも多くの事が出来ると思う	○	○	○	○	○
5.一般的に、自動車での移動は一番安全で安心できる交通手段だと思う	○	○	○	○	○
6.車を保有することは社会的地位のシンボルだ	○	○	○	○	○
7.渋滞対策として、新しい道路を建設する必要がある	○	○	○	○	○
8.渋滞と大気汚染の対策として、ガソリン価格を上げるべきだと思う	○	○	○	○	○

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Q17 以下の質問、公共交通について、あなたはどのように思いますか。それぞれお答えください。
【必須】 （矢印方向にそれぞれひとつだけ）

	1.そう思う	2.どちらかと言えばそう思う	3.どちらとも言えない	4.どちらかと言えばそう思わない	5.そう思わない
1.公共交通の車内では、読書や電子機器の操作など、自動車運転中にはできない色々な活動ができることが魅力だ	○	○	○	○	○
2.車を運転する費用より、公共交通を利用する費用の方が高い	○	○	○	○	○
3.バスや路面電車はよく遅れる、信頼性に欠ける	○	○	○	○	○
4.お金が十分にあれば、電車やバスには乗りたくない	○	○	○	○	○
5.バスや路面電車は乗り心地が良い	○	○	○	○	○
6.公共交通に乗ることは環境に優しい	○	○	○	○	○
	1.そう思う	2.どちらかと言えばそう思う	3.どちらとも言えない	4.どちらかと言えばそう思わない	5.そう思わない
7.歩くことが好き	○	○	○	○	○
8.自転車に乗ることが好き	○	○	○	○	○
9.できる限り、自動車よりも公共交通で移動するようにしている	○	○	○	○	○

10.できる限り、自動車より徒歩や自転車で移動するようにしている	○	○	○	○	○
11.公共交通を改善するために税金を投入することは、良いことだと思う	○	○	○	○	○

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Q18 【必須】 以下の質問、住宅環境について、あなたはどのように思いますか。それぞれお答えください。
（矢印方向にそれぞれひとつだけ）

	1. そう思う	2. どちらかと言えばそう思う	3. どちらとも言えない	4. どちらかと言えばそう思わない	5. そう思わない
1.隣の家との間隔は広い方がいいと思う	○	○	○	○	○
2.徒歩や自転車で行ける範囲内に様々な店舗があることは大切だと思う	○	○	○	○	○
3.マンションや集合住宅にできるだけ住みたくない	○	○	○	○	○
4.大きな商業施設の近くに住むことは大切だと思う	○	○	○	○	○
5.公共交通の利便性が高い地区に住むことは重要だと思う	○	○	○	○	○
6.公共交通の利便性が高い地区に住むよりも、広い家に住みたいと思う	○	○	○	○	○
	1. そう思う	2. どちらかと言えばそう思う	3. どちらとも言えない	4. どちらかと言えばそう思わない	5. そう思わない
7.家庭のためには、中心市街地より郊外に家を構えたいと思う	○	○	○	○	○
8.駐車場を確保しやすい地区に住みたいと思う	○	○	○	○	○
9.中心市街地に行きやすい地区に住みたいと思う	○	○	○	○	○
10.家が多少狭くても、色々な施設が近くにある地区に住みたいと思う	○	○	○	○	○
11.引越す時には、郊外に住むより、中心市街地の近くに住みたいと思う	○	○	○	○	○

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Q19 【必須】 以下の行き先に「家から」何回行くかを、それぞれお答えください。
（1日に朝夜などで2回行く場合は、複数回としてお考えください）
（矢印方向にそれぞれひとつだけ）

	まったく行	年に数回	月に数回	週に1回	週に2回	週に3回	週に4回	週に5回	週に6回	週に7回	週に8回	週に9回以

	かない											上
1.通勤通学先	○	○	○	○	○	○	○	○	○	○	○	○
2.スーパー	○	○	○	○	○	○	○	○	○	○	○	○
3.コンビニ	○	○	○	○	○	○	○	○	○	○	○	○
4.家電量販店、大型ショッピングモールなど	○	○	○	○	○	○	○	○	○	○	○	○
5.娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など	○	○	○	○	○	○	○	○	○	○	○	○
6.外食：食堂・レストラン・バー・居酒屋など	○	○	○	○	○	○	○	○	○	○	○	○
7.散歩することや公園へ行くこと	○	○	○	○	○	○	○	○	○	○	○	○
8.広島市中心部（紙屋町、大手町、広島駅付近など）	○	○	○	○	○	○	○	○	○	○	○	○
9.行政・文化施設：市役所・図書館など	○	○	○	○	○	○	○	○	○	○	○	○
10.病院・医院・福祉施設	○	○	○	○	○	○	○	○	○	○	○	○

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選択肢の引継ぎ

引継ぎ対象質問　：[不一致] Q19.「以下の行き先に「家から」何回行くかを…」でMT引継ぎ条件に一致していない質問アイテムを質問アイテムへ引継ぎ

引継ぎする質問アイテム：通勤通学先
スーパー
コンビニ
家電量販店、大型ショッピングモールなど
娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など
外食：食堂・レストラン・バー・居酒屋など
散歩することや公園へ行くこと
広島市中心部（紙屋町、大手町、広島駅付近など）
行政・文化施設：市役所・図書館など
病院・医院・福祉施設

引継ぎ条件　：まったく行かない

Q20 【必須】　それぞれの行き先に「家から」行く際に最も利用する交通手段をお選びください。
（矢印方向にそれぞれひとつだけ）

	1.自動車＜自分が運転＞	2.自動車＜家族や知り合いが運転＞	3.バイク	4.電車や路面電車	5.バス	6.自転車	7.徒歩	8.その他
1.通勤通学先 @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
2.スーパー @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
3.コンビニ @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
4.家電量販店、大型ショッピングモールなど @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
5.娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○

6.外食：食堂・レストラン・バー・居酒屋など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
7.散歩することや公園へ行くこと @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
8.広島市中心部（紙屋町、大手町、広島駅付近など）@@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
9.行政・文化施設：市役所・図書館など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○
10.病院・医院・福祉施設 @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○

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選択肢の引継ぎ

引継ぎ対象質問 ：[不一致] Q19.「以下の行き先に「家から」何回行くかを…」でMT引継ぎ条件に一致していない質問アイテムを質問アイテムへ引継ぎ

引継ぎする質問アイテム ：通勤通学先
スーパー
コンビニ
家電量販店、大型ショッピングモールなど
娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など
外食：食堂・レストラン・バー・居酒屋など
散歩することや公園へ行くこと
広島市中心部（紙屋町、大手町、広島駅付近など）
行政・文化施設：市役所・図書館など
病院・医院・福祉施設

引継ぎ条件 ：まったく行かない

Q21 【必須】 それぞれの行き先に「家から」行く際の平均所要時間をお選びください。（矢印方向にそれぞれひとつだけ）

	10分未満	10分～15分未満	15分～20分未満	20分～25分未満	25分～30分未満	30分～35分未満	35分～40分未満	40分～45分未満	45分～50分未満	50分～55分未満	55分～60分未満	60分以上
1.通勤通学先 @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
2.スーパー @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
3.コンビニ @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
4.家電量販店、大型ショッピングモールなど @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
5.娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
6.外食：食堂・レストラン・バー・居酒屋など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
7.散歩することや公園へ行くこと @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
8.広島市中心部（紙屋町、大手町、広島駅付近など）@@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
9.行政・文化施設：市役所・図書館など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○
10.病院・医院・福祉施設 @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○	○	○	○	○	○	○	○

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選択肢の引継ぎ

引継ぎ対象質問 : [不一致] Q19.「以下の行き先に「家から」何回行くかを...」でMT引継ぎ条件に一致していない質問アイテムを質問アイテムへ引継ぎ

引継ぎする質問アイテム : 通勤通学先
スーパー
コンビニ
家電量販店、大型ショッピングモールなど
娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など
外食：食堂・レストラン・バー・居酒屋など
散歩することや公園へ行くこと
広島市中心部（紙屋町、大手町、広島駅付近など）
行政・文化施設：市役所・図書館など
病院・医院・福祉施設

引継ぎ条件 : まったく行かない

Q22 【必須】 それぞれの行き先に「家から」行く際の平均所要時間に対する満足度をお答えください。
（矢印方向にそれぞれひとつだけ）

	1. 満足	2. やや満足	3. どちらでもない	4. やや不満	5. 不満
1.通勤通学先 @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
2.スーパー @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
3.コンビニ @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
4.家電量販店、大型ショッピングモールなど @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
5.娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
6.外食：食堂・レストラン・バー・居酒屋など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
7.散歩することや公園へ行くこと @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
8.広島市中心部（紙屋町、大手町、広島駅付近など） @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
9.行政・文化施設：市役所・図書館など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
10.病院・医院・福祉施設 @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○

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選択肢の引継ぎ

引継ぎ対象質問 : [不一致] Q19.「以下の行き先に「家から」何回行くかを...」でMT引継ぎ条件に一致していない質問アイテムを質問アイテムへ引継ぎ

引継ぎする質問アイテム : スーパー
コンビニ
家電量販店、大型ショッピングモールなど
娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など

外食：食堂・レストラン・バー・居酒屋など
散歩することや公園へ行くこと
広島市中心部（紙屋町、大手町、広島駅付近など）
行政・文化施設：市役所・図書館など
病院・医院・福祉施設
引継ぎ条件　：まったく行かない

Q23
【必須】
それぞれの行き先の充実度・品質に対する満足度をお答えください。
（矢印方向にそれぞれひとつだけ）

	1. 満足	2. やや満足	3. どちらでもない	4. やや不満	5. 不満
1.スーパー @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
2.コンビニ @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
3.家電量販店、大型ショッピングモールなど @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
4.娯楽・レジャー施設：映画館・カラオケ・スポーツ施設など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
5.外食：食堂・レストラン・バー・居酒屋など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
6.散歩することや公園へ行くこと @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
7.広島市中心部（紙屋町、大手町、広島駅付近など） @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
8.行政・文化施設：市役所・図書館など @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○
9.病院・医院・福祉施設 @@IMPORT@@（[不一致]Q19でMT引継ぎ条件に不一致の回答時に表示）	○	○	○	○	○

次へ

改ページ

Q24
【必須】
あなたがお住まいの地域についてお伺いします。
あなたは今のお住まいで生活する中で、以下の事柄を経験・実感されていますか。
（矢印方向にそれぞれひとつだけ）

	1. 経験・実感している	2. 少し経験・実感している	3. あまり経験・実感していない	4. 経験・実感していない
1.自動車を運転・利用（同乗）できなくなったこと	○	○	○	○
2.同居人数が増えた、子供が成長したなど、住居が手狭になったこと	○	○	○	○
3.同居人数が減った、子供が独立したなど、住居にゆとりができたこと	○	○	○	○
4.お住まいの近隣の空き地空き家が増加したこと	○	○	○	○
5.お住まいの近隣の人口が減少したこと	○	○	○	○

6.お住まいの近隣住民の若年層の人数が減少したこと	○	○	○	○
7.お住まいの近隣の公共交通の本数が減少したこと	○	○	○	○
8.お住まいの近隣の商業店舗や公共施設の数が減少したこと	○	○	○	○
9.お住まいの近隣の家賃・地価など、不動産相場が変化したこと	○	○	○	○

次へ

改ページ

Q25 【必須】 あなたがお住まいの地域についてお伺いします。
あなたは今のお住まいで生活する中で、将来的に以下の事柄が生じる可能性を意識されていますか。
（矢印方向にそれぞれひとつだけ）

	1. 意識している	2. 少し意識している	3. あまり意識していない	4. 意識していない
1.自動車を将来運転・利用（同乗）できなくなる可能性	○	○	○	○
2.同居人数が増える、子供が成長するなど、住居が将来手狭になる可能性	○	○	○	○
3.同居人数が減る、子供が独立するなど、住居に将来ゆとりができる可能性	○	○	○	○
4.お住まいの近隣の空き地空き家が将来増加して、住環境や治安が悪化する可能性	○	○	○	○
5.お住まいの近隣住民の人口が将来減少して、地域の活力が低下する可能性	○	○	○	○
6.お住まいの近隣住民の若年層の人数が将来減少して、地域の活力が低下する可能性	○	○	○	○
7.お住まいの近隣の公共交通の本数が将来減少して、利便性が低下する可能性	○	○	○	○
8.お住まいの近隣の商業店舗や公共施設の数や質が将来減少して、利便性が低下する可能性	○	○	○	○
9.お住まいの近隣の家賃・地価など、不動産相場が将来変化する可能性	○	○	○	○

次へ

改ページ

Q26 【必須】 あなたが小中学生時代に最も長く住んでいた場所はどんな所でしたか。

- ○ 1. 大都市圏（東京・大阪・名古屋）の中心部
- ○ 2. 大都市圏（東京・大阪・名古屋）の郊外
- ○ 3. 地方都市（広島含む）の中心部
- ○ 4. 地方都市（広島含む）の郊外
- ○ 5. 小都市（人口数万人）
- ○ 6. 村・集落
- ○ 7. 山奥・田舎
- ○ 8. その他（　　）（回答必須）

次へ

改ページ

Q27 【必須】 あなたが現在住んでいる所を選んだ人は誰ですか。

- ○ 1. ほぼ自分のみで判断・決定した
- ○ 2. 自分の意見が決め手となったが、家族や親戚などの意見も取り入れて判断・決定した
- ○ 3. 自分は意見を主張したが、家族や親戚などが主に判断・決定した
- ○ 4. 家族や親戚などが判断・決定し、自分は関わっていない（幼少より転居していない場合も含みます）
- ○ 5. 会社が選んだ
- ○ 6. 他の人が選んだ
- ○ 7. その他（　　）（回答必須）

次へ

改ページ

Q28 【必須】 世帯で自動車を持っているかどうか、また持っている場合は台数をお答えください。

- ○ 1台保有
- ○ 2台保有
- ○ 3台保有
- ○ 4台保有
- ○ 5台以上
- ○ 持っていない

次へ

改ページ

■以下の設問では、ご家族又はご自身で所有している自動車についての、
費用負担額や負担額のイメージについてお伺いします。

分岐条件

分岐条件式　　：（Q28 ornot 6）

Q29 【必須】 その自動車1台に対して、車両代や燃料費・税金・駐車場代・保険料・車検代金などすべて合わせて、
【一月当たりに換算すると】どの程度の費用がかかっていると思うかを、『直感で』お答えください。
（半角数字でご記入ください）

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

　　円【必須】（数字のみ）

次へ

改ページ

分岐条件

分岐条件式　　：（Q28 ornot 6）

Q30 【必須】 1カ月当たりに「その自動車1台のための」ガソリンにかかる費用は平均でどの程度かをお答えください。
（長期休暇等がない一般的な月でお考えください）

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

- ○ 0円～2,000円
- ○ 2,001円～5,000円
- ○ 5,001円～10,000円
- ○ 10,001円～15,000円

○ 15,001円～20,000円
○ 20,001円～
○ わからない

次へ

改ページ

分岐条件
分岐条件式　　:(Q28 ornot 6)

Q31
【必須】
1カ月当たりに「その自動車1台に対して(ご家族が行う給油も含め)」ガソリンスタンドで給油を行う回数は平均で何回程度かをお答えください。

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

○ 月1回未満
○ 月1回程度
○ 月2回程度
○ 月3回程度
○ 月4回程度
○ 月5回以上
○ わからない

次へ

改ページ

分岐条件
分岐条件式　　:(Q28 ornot 6)

Q32
【必須】
自動車のメーカー名と車種をお答えください。

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

【回答例】「トヨタ　ウィッシュ」「日産　キューブ」「ホンダ　フィット」 など【必須】(制限なし)

次へ

改ページ

分岐条件
分岐条件式　　:(Q28 ornot 6)

Q33
【必須】
自動車の総排気量(cc)をお答えください。

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

○ 1,000cc以下
○ 1,001～1,500cc以下
○ 1,501～2,000cc以下
○ 2,001～2,500cc以下
○ 2,501～3,000cc以下
○ 3,001～3,500cc以下
○ 3,501～4,000cc以下
○ 4,001～4,500cc以下
○ 4,501～6,000cc以下
○ 6,000cc超
○ わからない/知らない

次へ

改ページ

分岐条件

分岐条件式　　:(Q28 ornot 6)

Q34
【必須】
車両の重量をお答えください。

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

- ○ 0.5トン以下
- ○ 0.5トン超～1.0トン以下
- ○ 1.0トン超～1.5トン以下
- ○ 1.5トン超～2.0トン以下
- ○ 2.0トン超～2.5トン以下
- ○ 2.5トン超～3.0トン以下
- ○ 3.0トン超
- ○ わからない/知らない

次へ

改ページ

分岐条件

分岐条件式　　:(Q28 ornot 6)

Q35
【必須】
電気自動車、プラグインハイブリッド車、クリーンディーゼル車に該当するか否かをお答えください。

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

- ○ 1. 電気自動車
- ○ 2. プラグインハイブリッド車
- ○ 3. クリーンディーゼル車
- ○ 4. 上記の3種類には該当しない

次へ

改ページ

分岐条件

分岐条件式　　:(Q28 ornot 6)

Q36
【必須】
自動車の購入価格を10万円単位でお答えください。
(半角数字でご記入ください)

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

[　　] 万円【必須】(数字のみ)

次へ

改ページ

分岐条件

分岐条件式　　:(Q28 ornot 6)

Q37
【必須】
「その自動車1台のための」自動車保険の月額でのおおよその保険料を、千円単位でお答えください。
1年単位でお支払いの方も、一月当たりの金額でお答えください。
(半角数字でご記入ください)

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

月額 [　　] 円【必須】(数字のみ)

次へ

改ページ

分岐条件

分岐条件式　　:(Q28 ornot 6)

Q38
【必須】
「その自動車1台あたりの」1ヶ月当たりの走行距離は概ねどの程度かをお答えください。

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

- ○ 0km～200km
- ○ 201km～500km
- ○ 501km～1,000km
- ○ 1,001km～1,500km
- ○ 1,501km～2,000km
- ○ 2,001km～
- ○ わからない

次へ

改ページ

分岐条件

分岐条件式　　:(Q28 ornot 6)

Q39
【必須】
「その自動車の駐車を目的として」ご自宅以外に駐車場を借りているか否か、
借りている場合は有料か無料か、また有料の場合は月額でいくらかをお答えください。

※この設問では、複数台自動車を持っている場合には、
ご自身が主に利用している自動車1台についてお答えください。
世帯で1台だけ自動車を持っている場合には、その自動車についてお答えください。

- ○ 1. 借りていない
- ○ 2. 借りているが無料
- ○ 3. 借りていて有料(月額 [　　] 円)(回答必須)

次へ

改ページ

分岐条件

分岐条件式　　:(Q28 ornot 6)

Q40
【必須】
以下の項目に関して、そう思う～そう思わないの5段階でお選びください。
(矢印方向にそれぞれひとつだけ)

	1. そ	2. ど	3. ど	4. ど	5. そ

	う思う	ちらかと言えばそう思う	ちらとも言えない	ちらかと言えばそう思わない	う思わない
1.自動車に掛る維持費用が現在の2倍になったら、 自動車保有台数を減らして公共交通での移動やカーシェアリングに切り替えたい	○	○	○	○	○
2.自動車に掛る維持費用が現在の2倍になったら、 今よりも都心部への住み替えたい	○	○	○	○	○

次へ

改ページ

アンケートにご回答、ありがとうございます。

〇ポイント

獲得されたポイントは、翌月15日までに楽天スーパーポイントに付与されます。
モニター回答履歴には、翌日中に反映されます。
ポイントにつきましては、楽天スーパーポイントでご確認ください。

閉じる

個人情報保護方針

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MACROMILL

Q28

行動に関するアンケート【222406】

下記アンケートにご協力お願いいたします。

本調査にご協力いただき、誠にありがとうございます。

本調査は東京大学大学院工学系研究科都市工学専攻都市交通研究室が行っている
研究プロジェクトの一環として実施しています。
福岡市にお住まいの方を対象に、地区の特性及び人々の
社会的ネットワークが交通行動に与える影響を把握することが目的です。
回答にはおよそ30分程度かかります。

ご回答頂いた情報の秘密は守られ、第三者へ開示または提供することは絶対にありません。
また、データは集計されて分析されますので、あなた個人までさかのぼって
特定することはできません。
本調査の結果は当研究室の博士論文の一部として利用させていただくとともに、
国内のまたは国際的な学術雑誌に論文として投稿することを予定しています。

当アンケートの回答者の皆様へお願い

マクロミルモニタの皆様にはモニタ規約にて「調査についての守秘義務」の徹底をお願いしています。
当アンケートの内容および当アンケートで知りえた情報については、決して第三者に口外しないよう（掲示板やホームページへの書き込みを含む）、ご協力お願いします。

ここで改ページ

[QID]	q1
[原稿ID]	1
[質問タイプ]	SA　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	
[文言変更履歴]	
[ノート]	

Q1 **あなたは現在、あなたご自身を含めて何人で同居されていますか。**

- ○ 1人
- ○ 2人
- ○ 3人
- ○ 4人
- ○ 5人
- ○ 6人
- ○ 7人
- ○ 8人
- ○ 9人
- ○ 10人以上

ここで改ページ

Q2

[QID]	q2
[原稿ID]	2-5
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【表示制御】 q1で選択した人数まで表示 【回答制御】 ・「あなたご自身」の属性情報と異なる性別、年齢を回答した場合はアラート ・「年齢」で「0-17」を入力し、「自動車免許」で「持っている」を選択した場合アラート
[文言変更履歴]	
[FA設定]	2: (入力範囲):20-, 7: (入力範囲):0-120, 11: (入力範囲):0-120, 15: (入力範囲):0-120, 19: (入力範囲):0-120, 23: (入力範囲):0-120,

	27: (入力範囲):0-120, 31: (入力範囲):0-120, 35: (入力範囲):0-120, 39: (入力範囲):0-120,
[ノート]	

あなたと同居者全員の年齢、性別、自動車運転免許の有無、職業、副業をお答えください。

	性別	年齢	自動車免許	現在の職業	副業
あなたご自身	--	歳	--	--	--
同居している方1人目	--	歳	--	--	
同居している方2人目	--	歳	--	--	
同居している方3人目	--	歳	--	--	
同居している方4人目	--	歳	--	--	
同居している方5人目	--	歳	--	--	
同居している方6人目	--	歳	--	--	
同居している方7人目	--	歳	--	--	
同居している方8人目	--	歳	--	--	
同居している方9人目	--	歳	--	--	

ここで改ページ

[QID]	q3
[原稿ID]	6
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	q2_4=1-10 OR q2_5=2-10
[ロジック設定]	【表示制御】 q2「あなたご自身」の「現在の職業」で1-6,10、「副業」で2-7,10を選択した場合に「職場の住所」を表示 q2「あなたご自身」の「現在の職業」で7-9、「副業」で8-9を選択した場合に「学校の住所」を表示
[文言変更履歴]	
[ノート]	

現在の職場・学校の住所を町丁目までお答えください。
（○丁目という表示でない場合は「字」または町名までお答えください）
※記入例）
「福岡市博多区博多駅南4」
「福岡県福岡市早良区西」
「福岡県福岡市早良区脇山」

職場の住所
学校の住所

ここで改ページ

[QID]	q4
[原稿ID]	7
[質問タイプ]	SA　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	
[文言変更履歴]	
[ノート]	

あなたの最終学歴をお答えください。

- ○ 1. 中学校卒業
- ○ 2. 高等学校卒業
- ○ 3. 専門学校・短大卒業
- ○ 4. 大学（学部）卒業
- ○ 5. 大学院（修士）卒業
- ○ 6. 大学院（博士）卒業

ここで改ページ

[QID]	q5
[原稿ID]	8-9
[質問タイプ]	MTS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	
[文言変更履歴]	
[ノート]	

現在、世帯で自転車・自動車をそれぞれ何台お持ちですか。

	持っていない	1台	2台	3台	4台	5台	6台以上
自転車	○	○	○	○	○	○	○
自動車	○	○	○	○	○	○	○

ここで改ページ

[QID]	q6
[原稿ID]	10
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	q5_2=2-7
[ロジック設定]	
[文言変更履歴]	
[FA設定]	3: (入力範囲):1900-2013,
[ノート]	

あなたの世帯で主に利用している自動車1台について、メーカー名、車種名、製造年をお答えください。
電気自動車、ハイブリッド車、プラグインハイブリッド車の場合、車種名欄にその旨も記入してください。
※「製造年」がわからない場合は、車検証に記載されています。お手数ですが、車検証をご確認の上ご回答ください。

例：メーカー名：トヨタ
　車種名：プリウスプラグインハイブリッド
　製造年：2008年

メーカー名
車種名
製造年　　年

ここで改ページ

[QID]	q7
[原稿ID]	11
[質問タイプ]	MA　必須
[確認事項]	
[セレクト条件]	
[排他選択肢]	10. クラブや団体に所属していない
[ロジック設定]	
[文言変更履歴]	
[ノート]	

あなたのパーソナルコミュニティについてお伺いいたします。
あなたはクラブや団体に所属していますか。
所属している場合、下記の選択肢より、当てはまるものをお選びください。

☐ 1.　PTA（親と先生の会）
☐ 2.　スポーツクラブ（学校や職場の部活動・サークルは除く）

- ☐ 3. 美術・音楽・文学サークル（学校や職場の部活動・サークルは除く）
- ☐ 4. 勉強会
- ☐ 5. 学校や職場の部活動・サークル
- ☐ 6. 教会など宗教的な活動を行う団体
- ☐ 7. NPO、ボランティア団体等
- ☐ 8. 地域の自治会
- ☐ 9. その他
- ☐ 10. クラブや団体に所属していない

ここで改ページ

[QID]	q8
[原稿ID]	12
[質問タイプ]	MTS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【項目表示制御】 「所属しているクラブや団体」は、q7=1-9の場合表示
[文言変更履歴]	
[ノート]	

あなたの人付き合いについてお伺いいたします。
日頃親しくお付き合い（よく行き来したり、一緒に遊びに行ったり）している親戚、職場・学校の人、近所の人、友人はそれぞれ何人いますか。

	0人	1人	2人	3人	4人	5人	6人	7人	8人	9人	10人以上
親戚（同居家族は含む）	○	○	○	○	○	○	○	○	○	○	○ 人
職場・学校の人	○	○	○	○	○	○	○	○	○	○	○ 人
近所の人	○	○	○	○	○	○	○	○	○	○	○ 人
所属しているクラブや団体の人	○	○	○	○	○	○	○	○	○	○	○ 人
上記以外の友人	○	○	○	○	○	○	○	○	○	○	○ 人

ここで改ページ

[QID]	q9
[原稿ID]	13
[質問タイプ]	MTS　必須
[確認事項]	
[セレクト条件]	q8_1-5=2-11
[ロジック設定]	【項目表示制御】 q8で選択した人数の合計に合わせて表示 【選択肢表示制御】 q8で2-11を選択したもののみ表示 【回答制御】 ・各選択肢ごとに、q8で選択した数よりq9での選択数の合計が多い場合アラート ・「名前」は、全角カタカナで入力がない場合アラート ・「名前」に重複がある場合はアラート
[文言変更履歴]	
[ノート]	

前問でお答えいただいた日頃、同居家族以外であなたが最も親しいと考える人、上位5人思い浮かべください。
以下の中から、その5人の方にあてはまるものをお選びください。

※最も親しい5人の方は、順位を付けなくても問題ありません。
※「名前」の欄は全て全角カタカナでご回答ください。
※「名前」には、同一のお名前を入力することはできません。
■記入例
1人目：ミキチャン
2人目：ミドリチャン
3人目：ヤスイクン
※お名前については、愛称（あだ名）・本名のどちらでも問題ありません。

	親戚	職場・学校の人	近所の人	所属しているクラブや団体の人	それ以外の友人
1人目 名前あるいはあだ名	○	○	○	○	○
2人目 名前あるいはあだ名	○	○	○	○	○
3人目 名前あるいはあだ名	○	○	○	○	○
4人目 名前あるいはあだ名	○	○	○	○	○
5人目 名前あるいはあだ名	○	○	○	○	○

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[QID]	q28
[原稿ID]	62
[質問タイプ]	MTM　必須
[確認事項]	
[セレクト条件]	q9で2人以上いる場合表示
[排他選択肢]	6. この中には知り合い同士はいない
[ロジック設定]	
[文言変更履歴]	
[ノート]	

前問でお答え頂いたご友人・お知り合いの方々について引き続きお伺いします。
ご友人・お知り合いの方々同士はそれぞれお知り合いですか。

	q9_1_1faの回答	q9_2_1faの回答	q9_3_1faの回答	q9_4_1faの回答	q9_5_1faの回答	この中には知り合い同士はいない
q9_1_1faの回答	--	□	□	□	□	□
q9_2_1faの回答	--	--	□	□	□	□
q9_3_1faの回答	--	--	--	□	□	□
q9_4_1faの回答	--	--	--	--	□	□
q9_5_1faの回答	--	--	--	--	--	□

ここで改ページ

[QID]	q10
[原稿ID]	14
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	
[文言変更履歴]	
[ノート]	

あなたの現在のお住まいを町丁目まで(○丁目という表示でない場合は「字」または町名まで)お答えください。
※記入例)
「福岡市博多区博多駅南4」
「福岡県福岡市早良区西」
「福岡県福岡市早良区脇山」

ここで改ページ

[QID]	q11
[原稿ID]	15
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【回答制御】 ・上から順に回答が無い場合アラート ・同一の住所を入力した場合アラート
[文言変更履歴]	
[ノート]	

続いて、あなたの過去のお住まいについてお伺いいたします。
あなたがこれまでに住んだことがある住所を3ヶ所(町丁目まで)お答えください。
3ヶ所を超える場合、長く住んだ順にお住まいの住所をお答えください。
※海外に住んだことがある場合も、ご記入ください。
記入例)
「福岡市博多区博多駅南4」
「福岡県福岡市早良区西」
「福岡県福岡市早良区脇山」

※現在のお住まいは除いてご記入ください。
住んだことがある住所1つ目
住んだことがある住所2つ目
住んだことがある住所3つ目

☐ 生まれた時からずっと現在の住所に住んでいる

ここで改ページ

[QID]	q12
[原稿ID]	16-21
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【表側表示制御】 「住んだことがある」は、q11で入力がある場合表示 【回答制御】 ・「住み終えた年」は、生まれる前の年を入力した場合アラート ・「住み終えた年」は「住み始めた年」以上でない場合アラート ・各表側ごとに、2年以上住んでいる期間が重複している場合アラート ・「周辺環境」の「その他の内容」は「周辺環境」で「その他」を選択した場合に必須
[文言変更履歴]	
[FA設定]	1: (入力範囲):1900-2013, 8: (入力範囲):1900-2013, 9: (入力範囲):1900-2013, 15: (入力範囲):1900-2013, 16: (入力範囲):1900-2013, 22: (入力範囲):1900-2013, 23: (入力範囲):1900-2013,
[ノート]	

あなたがこれまでに住んだことがあるお住まいについて、
「住んでいた期間」「住まいのタイプ」「間取り」「周辺環境」「お引越し前の世帯での自動車保有台数」についてそれぞれご回答ください。

住み始めた年(西暦)	住み終えた年(西暦)	住まいのタイプ	間取り	どの場所	どの場所(その他)	当時の世帯での自動車保有台数

	住み始めた年（西暦）	住み終えた年（西暦）	住まいのタイプ	間取り	どの場所	どの場所（その他）	当時の世帯での自動車保有台数
現在のお住まい	年から	現在まで	--	--	--	その他の内容	--
（q11_1faの回答）	年から	年まで	--	--	--	その他の内容	--
（q11_2faの回答）	年から	年まで	--	--	--	その他の内容	--
（q11_3faの回答）	年から	年まで	--	--	--	その他の内容	--

ここで改ページ

[QID]	q13
[原稿ID]	22
[質問タイプ]	MTM 縦　必須
[確認事項]	
[セレクト条件]	q11_1-3のいずれかで回答あり
[排他選択肢]	1. この住まいより前に住んでいた家はない（一番最初の住まい） 11. 他の人が決めたため分からない 13. 特になかった
[ロジック設定]	【項目表示制御】 「住んだことがある」は、q11で入力がある場合表示 【回答制御】 「この住まいより前に住んでいた家はない（一番最初の住まい）」が2つ以上選択されている場合アラート
[文言変更履歴]	
[ノート]	

下記のお住まいにお引越しをした際に、引っ越しを決めたきっかけとなるライフイベント（就職、結婚、子供の誕生、転職等）がありましたか。

	現在のお住まい	q11_1faの回答	q11_2faの回答	q11_3faの回答
この住まいより前に住んでいた家はない（一番最初の住まい）	☐	☐	☐	☐
入学・転校・通学先の変更	☐	☐	☐	☐
就職・転職	☐	☐	☐	☐
失業	☐	☐	☐	☐
結婚	☐	☐	☐	☐
子供の誕生	☐	☐	☐	☐
子供の独立	☐	☐	☐	☐
離婚	☐	☐	☐	☐
昇進・昇給	☐	☐	☐	☐
退職	☐	☐	☐	☐
他の人が決めたため分からない	☐	☐	☐	☐
その他	☐	☐	☐	☐
特になかった	☐	☐	☐	☐

ここで改ページ

[QID]	q14
[原稿ID]	23-25
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【回答制御】 ・上から順に入力がない場合アラート ・各表側ごとに、いずれかに回答がある場合は表側ごと必須 ・「終了年」が「開始年」以上の場合アラート ・上から順に時系列になっていない場合アラート ・年齢と矛盾がある場合アラート
[文言変更履歴]	
[FA設定]	2: (入力範囲):1900-2013, 5: (入力範囲):1900-2013, 6: (入力範囲):1900-2013, 8: (入力範囲):1900-2013,

	9: (入力範囲):1900-2013, 11: (入力範囲):1900-2013, 12: (入力範囲):1900-2013, 14: (入力範囲):1900-2013, 15: (入力範囲):1900-2013,
[ノート]	

生まれてからこれまでに、あなたが主に利用してきた交通手段についてお答えください。

※回答例

	交通手段	開始年(西暦)	終了年(西暦)
1)現在最もよく利用する交通手段	自動車(主に自分で運転する)	2010 年から	現在まで
2)1の前に最もよく利用した交通手段	公共交通	2009 年から	2010 年まで
3)2の前に最もよく利用した交通手段	自転車	2005 年から	2008 年まで
4)3の前に最もよく利用した交通手段	徒歩	1995 年から	2005 年まで
5)4の前に最もよく利用した交通手段	--	年から	年まで

	交通手段	開始年(西暦)	終了年(西暦)
1)現在最もよく利用する交通手段	--	年から	現在まで
2)1の前に最もよく利用した交通手段	--	年から	年まで
3)2の前に最もよく利用した交通手段	--	年から	年まで
4)3の前に最もよく利用した交通手段	--	年から	年まで
5)4の前に最もよく利用した交通手段	--	年から	年まで

ここで改ページ

[QID]	q15
[原稿ID]	26
[質問タイプ]	MTS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	
[文言変更履歴]	
[ノート]	

あなたの交通に関する習慣、交通行動、ライフスタイルについてお伺いいたします。
以下の行動を行う際、どの交通手段を利用しますか。直感的にお答えください。
（あまり行かない場所についても、「もし行くことになったら」という想定でお答えください）

	自動車	公共交通	自転車	徒歩	バイク	その他
スーパーに行く時	○	○	○	○	○	○
市外に住んでいる友達を訪問する時	○	○	○	○	○	○
コンビニへ行く時	○	○	○	○	○	○
海へ行く時	○	○	○	○	○	○
スキーリゾートに行く時	○	○	○	○	○	○
公園に行く時	○	○	○	○	○	○
温泉に行く時	○	○	○	○	○	○
映画を見に行く時	○	○	○	○	○	○
レストランに夕飯を食べに行く時	○	○	○	○	○	○
洋服を買いに行く時	○	○	○	○	○	○

ここで改ページ

[QID]	q16
[原稿ID]	27
[質問タイプ]	MTS　必須
[確認事項]	
[セレクト条件]	

[ロジック設定]	
[文言変更履歴]	
[ノート]	

以下の質問について、あなたはどのように思いますか。それぞれお答えください。

	そう思わない	どちらかと言えばそう思わない	どちらとも言えない	どちらかと言えばそう思う	そう思う
自動車について					
車を運転することで自由を感じる	○	○	○	○	○
車を運転することが好き	○	○	○	○	○
車の運転をやめるより、電気自動車など環境に優しい自動車に変えた方がいいと思う	○	○	○	○	○
車を運転することでさらに多くの事が出来ると思う	○	○	○	○	○
一般的に、自動車は一番安全な交通手段だと思う	○	○	○	○	○
車を保有することは社会的地位のシンボルだ	○	○	○	○	○
渋滞対策として、新しい道路を建設する必要がある	○	○	○	○	○
渋滞と大気汚染の対策として、ガソリン価格を上げるべきだと思う	○	○	○	○	○

	そう思わない	どちらかと言えばそう思わない	どちらとも言えない	どちらかと言えばそう思う	そう思う
自動車以外について					
公共交通の車内では、読書や電子機器の操作など、自動車運転中にはできない色々な活動ができることが魅力だ	○	○	○	○	○
車を運転する費用より、公共交通を利用する費用の方が高い	○	○	○	○	○
バスや電車はよく遅れる、信頼性に欠ける	○	○	○	○	○
公共交通は貧しい人のためのものだと思う	○	○	○	○	○
バスや電車は乗り心地が良い	○	○	○	○	○
公共交通に乗ることは環境に優しい	○	○	○	○	○
歩くことが好き	○	○	○	○	○
自転車に乗ることが好き	○	○	○	○	○
出来る限り、自動車よりも公共交通で移動するようにしている	○	○	○	○	○
出来る限り自動車より徒歩や自転車で移動するようにしている	○	○	○	○	○
公共交通を改善するために税金を投入することは良いことだと思う	○	○	○	○	○

	そう思わない	どちらかと言えばそう思わない	どちらとも言えない	どちらかと言えばそう思う	そう思う
住宅環境について					
隣の家との間隔は広い方がいいと思う	○	○	○	○	○
徒歩や自転車で行ける範囲内に様々な店舗があることは大切だと思う	○	○	○	○	○
マンションや集合住宅に出来るだけ住みたくない	○	○	○	○	○
大型ショッピングモールの近くに住むことは大切だと思う	○	○	○	○	○
公共交通の利便性が高い地区に住むことは重要だと思う	○	○	○	○	○
公共交通の利便性が高い地区に住むよりも、広い家に住みたいと思う	○	○	○	○	○
家庭のためには、中心市街地より郊外の方がいい場所だ	○	○	○	○	○

駐車場を確保しやすい地区に住みたいと思う	○	○	○	○	○
中心市街地に行きやすい地区に住みたいと思う	○	○	○	○	○
家が多少狭くても色々な施設が近くにある地区に住みたいと思う	○	○	○	○	○
引越す時には、郊外に住むより、中心市街地の近くに住みたいと思う	○	○	○	○	○

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[QID]	q17
[原稿ID]	28-30
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【表示制御】 q2「あなたご自身」の「現在の職業」で1-6,10、「副業」で2-7,10を選択した場合に「通勤」を表示 q2「あなたご自身」の「現在の職業」で7-9、「副業」で8-9を選択した場合に「通学」を表示
[文言変更履歴]	
[FA設定]	1: (入力範囲):0-7, 3: (入力範囲):0-24, 4: (入力範囲):0-7, 6: (入力範囲):0-24,
[ノート]	

次からはあなたの交通行動及び社交活動についてお伺いいたします。

あなたは1週間に何回通勤・通学しますか。
あなたは通勤・通学の際、最も頻繁に使う交通手段はどれですか。
あなたは1日に働く時間、あるいは勉強する時間はおよそ何時間ですか。

	1週間の通勤・通学回数	交通手段	1日あたりの勤務時間・勉強時間
通勤	回	--	時間
通学	回	--	時間

ここで改ページ

[QID]	q18
[原稿ID]	31
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	q5_2=2-7
[ロジック設定]	
[文言変更履歴]	
[FA設定]	1: (入力範囲):0-,
[ノート]	

ご自宅で最も利用している自動車で、一週間でどの程度走行しますか。
※同乗した場合も含め、「最も利用している自動車」の年間走行距離をご回答ください。

km

☐ 全く見当がつかない

ここで改ページ

[QID]	q19
[原稿ID]	32
[質問タイプ]	MTS　必須
[確認事項]	

[セレクト条件]	
[ロジック設定]	【項目表示制御】 「通勤先・通学先から日用品を買いに行くこと「スーパー、コンビニ、薬局等」」 「通勤先・通学先から私用処理しに行くこと「銀行、郵便局、市役所、病院など」」 の各カテゴリーは、q2の「現在の職業」で1-6,8-10、「副業」で2-10を選択した場合に表示 【回答制御】 「全体での回数」と「自転車・バイクで」～「自転車・徒歩で」の合計が一致しない場合アラート
[文言変更履歴]	
[ノート]	

下記の移動について、過去1週間に行った頻度及び使った交通手段をお答えください。
次の設問は各項目の回答選択肢は下記通りです。

	0回	1回	2回	3回	4回	5回	6回	7回	8回	9回	10回以上
家から日用品を買いに行くこと「スーパー、コンビニ、薬局等」											
全体での回数	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自動車・バイクで	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、公共交通で	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自転車・徒歩で	○	○	○	○	○	○	○	○	○	○	○ 回
通勤先・通学先から日用品を買いに行くこと「スーパー、コンビニ、薬局等」											
回数	○	○	○	○	○	○	○	○	○	○	○ 回

	0回	1回	2回	3回	4回	5回	6回	7回	8回	9回	10回以上
家から私用処理しに行くこと「銀行、郵便局、市役所、病院など」											
全体での回数	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自動車・バイクで	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、公共交通で	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自転車・徒歩で	○	○	○	○	○	○	○	○	○	○	○ 回
通勤先・通学先から私用処理しに行くこと「銀行、郵便局、市役所、病院など」											
回数	○	○	○	○	○	○	○	○	○	○	○ 回

ここで改ページ

[QID]	q20
[原稿ID]	33
[質問タイプ]	MTS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【回答制御】 「全体での回数」と「自転車・バイクで」～「自転車・徒歩で」の合計が一致しない場合アラート
[文言変更履歴]	
[ノート]	

下記の活動について、過去2週間に行った頻度及び使った交通手段をお答えください。

	0回	1回	2回	3回	4回	5回	6回	7回	8回	9回	10回以上
日用品以外の買物（洋服・家電など）											
全体での回数	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自動車・バイクで	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、公共交通で	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自転車・徒歩で	○	○	○	○	○	○	○	○	○	○	○ 回
娯楽・レジャー（カラオケ・映画・演劇・スポーツ試合観戦・スポーツの練習・散歩等）											
全体での回数	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自動車・バイクで	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、公共交通で	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自転車・徒歩で	○	○	○	○	○	○	○	○	○	○	○ 回
	0回	1回	2回	3回	4回	5回	6回	7回	8回	9回	10回以上
外飲食（宴会、飲み会、忘年会、パーティ等）											
全体での回数	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自動車・バイクで	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、公共交通で	○	○	○	○	○	○	○	○	○	○	○ 回
そのうち、自転車・徒歩で	○	○	○	○	○	○	○	○	○	○	○ 回

ここで改ページ

[QID]	q100
[原稿ID]	プログラム用設問
[質問タイプ]	Caption　必須
[確認事項]	
[セレクト条件]	常に非表示
[ロジック設定]	
[文言変更履歴]	
[ノート]	

ここで改ページ

[QID]	q22

[原稿ID]	35-39
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【表示制御】 活動1～2は、以下の条件にて決定する q20で「1回」～「10回以上」を選択したものからランダムに2つ抽出 「1回」～「10回以上」を選択した活動カテゴリが2つ以上の場合は 2つの活動カテゴリから抽出 【回答制御】 ・「時間」で「24」を選択した場合は、「分」で「00」以外を選択した場合アラート ・「時間」で「0」を選択した場合は、「分」で「00」を選択した場合アラート
[文言変更履歴]	
[FA設定]	7: (入力範囲):1-, 16: (入力範囲):1-, 25: (入力範囲):1-, 34: (入力範囲):1-, 43: (入力範囲):1-, 52: (入力範囲):1-,
[ノート]	

過去2週間以内に行った活動について、詳しくお伺いします。
過去2週間以内に行った以下の各活動の、平日/休日・活動時間・活動の決め方・活動場所・活動場所への訪問頻度・人数・(レジャー/外飲食の内容)についてご回答ください。
※各活動は、それぞれ直近で行なったものから順にご回答ください。
※店舗や名所、公共施設等の住所が分からない場合、施設の名前と地区をお答えください。
例:「海鮮王国 天神店」

	活動日	活動合計時間(時)	活動合計時間(分)	決め方	活動場所の住所	活動場所への訪問頻度	一緒に活動を行った人数(あなたを含む)	レジャー/外飲食の内容
日用品以外の買物1	--	-- 時間	-- 分	--		--	人	--
日用品以外の買物2	--	-- 時間	-- 分	--		--	人	--
娯楽・レジャー1	--	-- 時間	-- 分	--		--	人	--
娯楽・レジャー2	--	-- 時間	-- 分	--		--	人	--
外飲食1	--	-- 時間	-- 分	--		--	人	--
外飲食2	--	-- 時間	-- 分	--		--	人	--

[QID]	q23
[原稿ID]	40-45
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【表示制御】 活動1～2は、以下の条件にて決定する q20で「1回」～「10回以上」を選択したものからランダムに2つ抽出 「1回」～「10回以上」を選択した活動カテゴリが2つ以上の場合は 2つの活動カテゴリから抽出 【選択肢表示制御】 「どこから」の選択肢「通勤先から」は、q2の「現在の職業」で1-6,10、「副業」で2-7,10を選択した場合に表示 「どこから」の選択肢「通学先から」は、q2の「現在の職業」,「副業」で8-9を選択した場合に表示
[文言変更履歴]	
[FA設定]	4: (入力範囲):0-, 8: (入力範囲):0-, 12: (入力範囲):0-, 16: (入力範囲):0-, 20: (入力範囲):0-, 24: (入力範囲):0-,
[ノート]	

過去2週間以内に行った活動について、詳しくお伺いします。
過去2週間以内に行った以下の各活動の、「どこから目的地に行ったか」「その際の交通手段」「移動時間」「移動距離」「同行した人数」をご回答ください。
※各活動は、それぞれ直近で行なったものから順にご回答ください。

どこから	どこから(その他)	交通手段	移動時間

		※「その他」を選択した場合のみご回答ください。		
日用品以外の買物1	--		--	分
日用品以外の買物2	--		--	分
娯楽・レジャー1	--		--	分
娯楽・レジャー2	--		--	分
外飲食1	--		--	分
外飲食2	--		--	分

ここで改ページ

[QID]	q24
[原稿ID]	45
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	q23のいずれかの人数で2以上を入力
[ロジック設定]	【回答欄表示制御】 各活動カテゴリーごとに、q22の「人数」の回答に合わせてFAを表示 【選択肢表示制御】 プルダウン内の選択肢は、q9のFAの内容を表示 【回答制御】 ・FA欄は全て全角カタカナでない場合アラート ・各活動内で、同じ選択肢を選択した場合アラート
[文言変更履歴]	
[ノート]	

過去2週間以内に行った活動について、詳しくお伺いします。
過去2週間以内に行った以下の各活動は、誰と一緒にいましたか。
■記入例
1人目：オカアサン
2人目：ミドリチャン
3人目：ヤスイクン
※同じ人は複数の活動内容に記入して問題ありません。但し、同じ方の名前は統一してご記入ください。
（同一人物で「ノリクン」「ノリチャン」など、異なる表記にならないようにご注意ください。）
※お名前については、愛称（あだ名）・本名のどちらでも問題ありません。
※各活動は、それぞれ直近で行なったものから順にご回答ください。
※全て全角カタカナでご回答ください

	1人目	1人目 その他の 名前またはあだ名	2人目	2人目 その他の 名前またはあだ名	3人目	3人目 その他の 名前またはあだ名	4人目
日用品以外の買物1	お選びください		お選びください		お選びください		お選びください
日用品以外の買物2	お選びください		お選びください		お選びください		お選びください
娯楽・レジャー1	お選びください		お選びください		お選びください		お選びください
娯楽・レジャー2	お選びください		お選びください		お選びください		お選びください
外飲食1	お選びください		お選びください		お選びください		お選びください
外飲食2	お選びください		お選びください		お選びください		お選びください

ここで改ページ

[QID]	q200
[原稿ID]	プログラム用設問
[質問タイプ]	Caption　必須
[確認事項]	
[セレクト条件]	常に非表示
[ロジック設定]	
[文言変更履歴]	
[ノート]	

ここで改ページ

[QID]	q25
[原稿ID]	47-52
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	q23のいずれかの人数で2以上を入力
[ロジック設定]	【表示制御】 友人1～5は、以下の条件にて決定する ・条件1：同じ名前は削除 ・条件2：優先順位が高い活動から3名抽出 （同じ活動内では前優先で抽出） ・条件3：優先順位が低い活動から5名になるまで抽出 ・条件4：5名に満たない場合は、抽出された名前と重複しないことを条件に ランダムでq9から5名になるまで抽出 【項目表示制御】 抽出された友人の名前が、q9で入力されたものの場合「関係」「続柄」は非表示 【選択肢表示制御】 ・q7=1-9の場合、「続柄」の「クラブのメンバー」を表示 【回答制御】 ・「年齢」で「0～9歳」を選択し、「自動車運転状況」で「運転する」を選択した場合アラート ・「続柄」で「配偶者」を2つ以上選択した場合アラート
[文言変更履歴]	
[ノート]	

前問でお答え頂いたご友人・お知り合いの方々について詳しくお伺いします。
ご友人・お知り合いの「性別」「年齢」「自動車運転状況」「ご関係」「続柄」「知り合った年」についてご回答ください。

	性別	年齢	自動車運転状況	関係	続柄	いつからの知り合いか
友達1	--	-- 歳	--	--	--	--
友達2	--	-- 歳	--	--	--	--
友達3	--	-- 歳	--	--	--	--
友達4	--	-- 歳	--	--	--	--
友達5	--	-- 歳	--	--	--	--

ここで改ページ

[QID]	q26
[原稿ID]	53-60
[質問タイプ]	FAS　必須
[確認事項]	
[セレクト条件]	q23のいずれかの人数で2以上を入力
[ロジック設定]	【表示制御】 友人1～5は、以下の条件にて決定する ・条件1：同じ名前は削除 ・条件2：優先順位が高い活動から3名抽出 （同じ活動内では前優先で抽出） ・条件3：優先順位が低い活動から5名になるまで抽出 ・条件4：5名に満たない場合は、抽出された名前と重複しないことを条件に ランダムでq9から5名になるまで抽出
[文言変更履歴]	
[FA設定]	2: (入力範囲):1-, 4: (入力範囲):1-, 6: (入力範囲):1-, 8: (入力範囲):1-, 10: (入力範囲):1-, 12: (入力範囲):1-, 14: (入力範囲):1-, 16: (入力範囲):1-, 18: (入力範囲):1-, 20: (入力範囲):1-, 22: (入力範囲):1-, 24: (入力範囲):1-, 26: (入力範囲):1-, 28: (入力範囲):1-, 30: (入力範囲):1-, 32: (入力範囲):1-,

	34: (入力範囲):1-, 36: (入力範囲):1-, 38: (入力範囲):1-, 40: (入力範囲):1-,
[ノート]	

前問でお答え頂いたご友人・お知り合いの方々について引き続きお伺いします。
ご友人・お知り合いと「直接会う頻度」「電話する頻度」「eMailの頻度」「SMS/インスタントメッセージの頻度」についてそれぞれご回答ください。
【 回答例 】
・年に10回の場合 ⇒ 単位で「年」、回数で「10」
・月に3回の場合 ⇒ 単位で「年」、回数で「10」
・0回の場合 ⇒ 単位で「なし」を選択

	直接会う頻度(単位)	直接会う頻度(回数)	電話する頻度(単位)	電話する頻度(回数)	eMailの頻度(単位)	eMailの頻度(回数)	SMS/インスタントメッセージの頻度(単位)	SMS/インスタントメッセージの頻度(回数)
友達1	--	回	--	回	--	回	--	回
友達2	--	回	--	回	--	回	--	回
友達3	--	回	--	回	--	回	--	回
友達4	--	回	--	回	--	回	--	回
友達5	--	回	--	回	--	回	--	回

ここで改ページ

[QID]	q27
[原稿ID]	61
[質問タイプ]	FAS 必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	【表示制御】 友人1～5は、以下の条件にて決定する ・条件1：同じ名前は削除 ・条件2：優先順位が高い活動から3名抽出 （同じ活動内では前優先で抽出） ・条件3：優先順位が低い活動から5名になるまで抽出 ・条件4：5名に満たない場合は、抽出された名前と重複しないことを条件に ランダムでq9から5名になるまで抽出 【回答制御】 ・「住所」は「お住まい」で「地区外に住んでる」を選択した場合必須
[文言変更履歴]	
[ノート]	

前問でお答え頂いたご友人・お知り合いの方々について引き続きお伺いします。
ご友人・お知り合いの「お住まい」と「住所」についてそれぞれご回答ください。

	お住まい	住所 **※「お住まい」で「地区外に住んでる」を選択した場合にご回答ください。**
友達1	--	
友達2	--	
友達3	--	
友達4	--	
友達5	--	

ここで改ページ

[QID]	q29
[原稿ID]	63
[質問タイプ]	SA 必須
[確認事項]	
[セレクト条件]	
[ロジック設定]	
[文言変更履歴]	

[ノート]	

あなたの世帯年収はおおよそいくらですか。以下の選択肢よりお選びください。

- ○ 200万円以下
- ○ 201万円～300万円
- ○ 301万円～400万円
- ○ 401万円～500万円
- ○ 501万円～600万円
- ○ 601万円～700万円
- ○ 701万円～800万円
- ○ 801万円～900万円
- ○ 901万円～1000万円
- ○ 1001万円～1200万円
- ○ 1201万円以上

内容をよく確認のうえ、【次へ】ボタンを押してください。
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次　へ

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