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Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings

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ABSTRACT *Numerous studies have found that suburban residents drive more and walk less than residents in traditional neighbourhoods. What is less well understood is the extent to which the observed patterns of travel behaviour can be attributed to the residential built environment (BE) itself, as opposed to attitude-induced residential self-selection. To date, most studies addressing this self-selection issue fall into nine methodological categories: direct questioning, statistical control, instrumental variables, sample selection, propensity score, joint discrete choice models, structural equations models, mutually dependent discrete choice models and longitudinal designs. This paper reviews 38 empirical studies using these approaches. Virtually all of the studies reviewed found a statistically significant influence of the BE remaining after self-selection was accounted for. However, the practical importance of that influence was seldom assessed. Although time and resource limitations are recognized, we recommend usage of longitudinal structural equations modelling with control groups, a design which is strong with respect to all causality requisites.*

Introduction

Suburban development has been widely criticized for its contribution to auto dependence and its consequences: air pollution, global climate change and oil dependence. Numerous studies have observed that residents of higher-density, mixed-use ('traditional', 'neo-traditional' or 'new urbanist') neighbourhoods tend to walk more and drive less than do inhabitants of lower-density, single-use residential ('suburban') areas (e.g. Crane and Crepeau, 1998; Cervero and Duncan, 2003; Frank *et al.*, 2006). As a result, some communities in the USA have adopted land use and transportation policies to promote those alternative developments, to counter sprawl and its negative effects. Most recently, policy-makers at the state level as well as at the local level have been considering land use policies as a way to reduce vehicle-miles travelled (VMT) and thus greenhouse

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gas emissions. The recent report *Growing Cooler* (Ewing *et al.*, 2008) summarizes the evidence on urban development and climate change and concludes that "it is realistic to assume a 30 percent cut in VMT [for people in areas of] compact development" (p. 9).

However, association does not necessarily mean causality; residential self-selection may confound the association between the built environment (BE) and travel behaviour (TB). For example, residents who prefer walking may consciously choose to live in neighbourhoods conducive to walking, and thus walk more. The self-selection issue relates to the question of spurious associations: Do the observed associations between the BE and TB reflect a true impact of the BE on behaviour or do they reflect a spurious association attributable to the simultaneous effect of preferences on both the choice of residential location (and thus BE) and TB? In the latter (admittedly extreme) case, an individual's TB depends not at all on the environment in which he finds himself—he will walk or drive regardless; we observe the association because the kind of people who like to walk also like to live in walking-oriented places.

The goal of research regarding self-selection is to establish whether there is a causal relationship between the BE and TB, and ultimately to determine the magnitude of this relationship. Such evidence provides a basis for the adoption of policies that aim to change TB by changing the BE. The existence of self-selection doesn't mean that the BE is irrelevant, but it must be accounted for in estimating the effect of the BE on TB if we want to be able to produce valid estimates of the impact of land use policies on behaviour. To the extent self-selection exists but is not accounted for, we are likely to misestimate the influence of BE elements when we use land use policies to try to reduce travel, fuel consumption and emissions. If, for example, someone with an automobile-oriented lifestyle ends up living in a dense, mixed-use neighbourhood (perhaps because of financial incentives or because not enough other housing is available to fulfil her preferences), her TB will probably not match that of those who actively want and choose to live in such neighbourhoods (Schwanen and Mokhtarian, 2005b). This points to the importance of understanding the demand for alternative developments. If (in contrast to the example) there is an unmet demand for such developments, expanding their supply may enable people living in suburban areas to move to places that better match their preferences—in other words, to self-select. Once there, the environment enables them to act on their preferences by walking more and driving less. For those people, the benefits from policies supporting alternative development may meet or even exceed expectations.

These estimation errors are likely to be greater in locations (such as the USA) where land use planning is local and to a large degree market-oriented, than in locations where the supply of various types of housing and residential densities is more centrally planned and tightly regulated. Even in the latter case, however, auto-oriented residents can show a considerable degree of attachment to the automobile in the face of policies that attempt to constrain (but do not altogether prohibit) the use of an automobile or promote the use of travel alternatives (e.g. Tertoolen *et al.*, 1998; Thøgersen and Møller, 2008). Thus, understanding how travel- and land use-related attitudes interact with the BE to influence TB is important in any event, to enable a more accurate assessment of the impact of land use policies on travel.

In the past few years, this complex issue has been addressed in a variety of ways, using methodologies which can be classified into nine categories. This

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paper reviews recent empirical studies within each category, focusing on data, variables, specific methodology, empirical results and the strengths or weaknesses of each study. By reviewing empirical findings on residential self-selection, this paper fills a gap left by previous papers. A companion paper (Mokhtarian and Cao, 2008) focuses more heavily on methodological approaches, assessing the strengths and weaknesses of each *approach* rather than each *study* and without presenting empirical findings from specific studies.[1] In contrast, Ewing and Cervero (2001), for example, reviewed more than 50 studies that explored the influences of BE elements (such as design and land use patterns) on several dimensions of TB (such as trip length and frequency) but they did not distinguish whether a study aims to test an association or a causal relationship. We pick up where these papers leave off, by focusing on empirical results from studies that explicitly address the question: to what degree are observed associations between the BE and TB explained by residential self-selection?

The organization of this paper is as follows: the 'Description of the Self-Selection Problem' section briefly reviews the conceptual and econometric bases of the self-selection problem; the 'Empirical Studies by Methodology' section discusses the various recent empirical studies that have addressed this issue; and the last section, 'Conclusions and Recommendations', summarizes the review and makes some recommendations for future research.

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Description of the Self-Selection Problem

As indicated earlier, previous studies have consistently found a significant association between the BE and TB. However, association itself is insufficient to establish causality. To *robustly* infer causality, scientific research generally requires at least four kinds of evidence (Schutt, 2004; Singleton and Straits, 2005): *association* (a statistically significant relationship), *non-spuriousness* (a relationship that cannot be attributed to another variable), *time precedence* (cause precedes effect) and *causal mechanism* (a logical explanation for why the alleged cause should produce the observed effect). (Refer to Cao *et al.* (2008) for a detailed discussion on the requisites for causal inference in the context of the BE and TB.)

Experimental design is the key to establishing these evidential components. In this context, however, the classic before-after random-assignment control group experimental design is impractical because of its prohibitive costs, ethical deficiency and/or political impossibility. As an alternative, some studies compared changes in TB between individuals who moved to an environment substantially different from their previous neighbourhoods (treatment group) and those who did not move (e.g. Krizek, 2003a). However, residential relocation is not a treatment randomly assigned by experimenters, but is a 'self-selected' result of individuals' changes in employment location, lifecycle and, importantly, attitudes towards travel. By contrast, another type of temporal change, a deliberate policy intervention (such as creating and promoting safe routes to school), is to some extent an experimental manipulation. However, intervention programmes are implemented at specific locations, which themselves are generally not random but rather (often) chosen on the basis of being more deficient on the dimension that the intervention is expected to improve. Further, participants are automatically classified into the treatment or control group based on their residential locations, not randomly assigned.

On the other hand, numerous studies employed cross-sectional data in lieu of longitudinal data capturing such changes in circumstance, but an overwhelming majority were built upon observational design, in which non-random assignment/selection bias is a major concern (Mokhtarian and Cao, 2008). In practice, if selection bias cannot be eliminated through study design, etiological analysis should be applied (Oakes, 2004). In other words, if an observational study attempts to ascertain the extent to which the BE *causes* TB, the goal is to use a methodology that is as robust as circumstances will permit with respect to the four types of evidence. It is particularly important to ensure that an observed association between BE and TB is not the spurious result of the fact that unmeasured attitudes are causing both. As shown in Figure 1, there are in fact a number of plausible relationships among attitudes, BE and TB, and the chosen methodology will ideally be capable of distinguishing among the various possibilities.

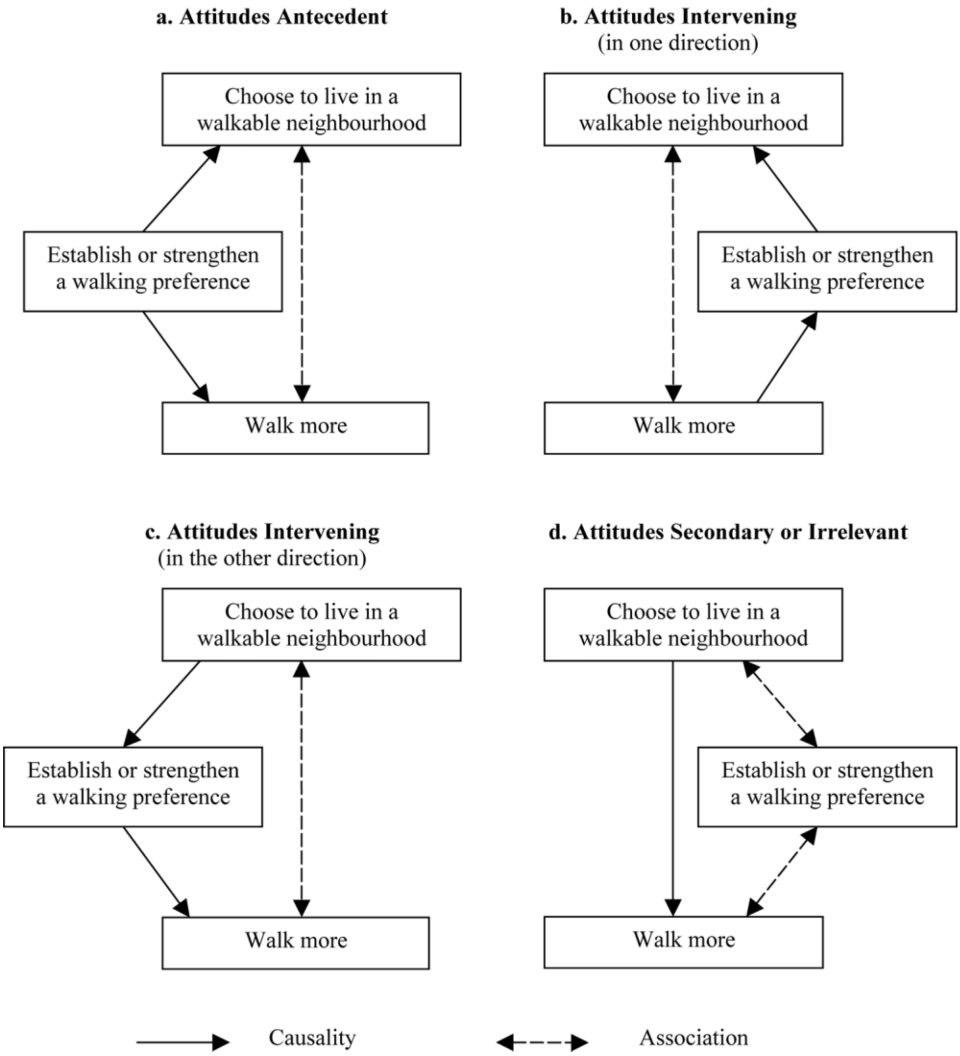

Figure 1. Some potential relationships among travel attitudes, built environment and travel behaviour

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Self-selection in this context refers to "the tendency of people to choose locations based on their travel abilities, needs and preferences" (Litman, 2005, p. 6). Residential self-selection generally results from two sources: attitudes and socio-demographic traits. An example of self-selection tied to socio-demographics occurs when low-income and zero-vehicle households choose to live in neighbourhoods with ample transit service and hence use transit more. In this case, it is not good transit facilities but households' economic constraints that have a true and direct influence on their choice of transit mode. However, since most studies have employed multivariate analysis and accounted for the sorting effect of socio-demographic characteristics (e.g. Kitamura *et al.*, 2001; Abreu e Silva *et al.*, 2006; van Acker *et al.*, 2007), we focus this review on the issue of attitude-induced self-selection. In simple mathematical terms, the often-observed relationship between BE and TB is generally modelled as taking the form:

$$TB = f(BE, X) + \varepsilon \tag{1}$$

where X denotes other observed variables such as socio-demographics, and ε represents the collective influence on TB of all unobserved variables. The problem is that the standard estimation of such functional forms requires that observed explanatory variables (BE, X) be uncorrelated with unobserved explanatory variables (ε). Failure to meet this important condition is broadly referred to as *endogeneity bias*, and produces coefficients for BE and X that are biased and inconsistent estimators of the true values. Furthermore, the conventionally estimated standard errors of the estimated coefficients will also be biased, which renders invalid the usual hypothesis-testing on the significance of variables (Ramanathan, 2002). In other words, this problem will occur if relevant attitudes are unmeasured and if they also influence residential location, in effect influencing what BE characteristics are experienced by the individual.

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Empirical Studies by Methodology

A number of approaches have been applied to address this endogeneity bias; we discuss 38 empirical studies, which collectively have taken nine such approaches. We identified the studies to include based on our knowledge and our connections with worldwide scholars in the field, but do not claim that they are exhaustive. Most studies are from North America, though five are based on European data. Most studies are published in the TB literature; a few studies from the field of physical activity are included because they convey important concepts. Table 1 summarizes the studies reviewed, grouped by methodology.

Direct Questioning

To assess whether people's travel and land use predispositions influenced their choice of residential neighbourhood, why not just ask them? Using 1368 respondents to a 1995 survey conducted in six neighbourhoods in Austin, TX, Handy and Clifton (2001) investigated the potential of providing local shopping as a strategy to reduce auto dependence. Following the survey, they conducted eight focus-group discussions with a total of 75 residents. They found some evidence for residential self-selection and concluded that "having the option to walk to the store is to some extent an effect of the desire to walk to the store" (p. 344).

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Table 1. Overview of studies addressing residential self-selection

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Direct questioning						
Hammond, 2005	90 respondents and 8 interview participants in Century Wharf, Cardiff, UK, 2004	Descriptive and correlational analyses	Changes in car use to work	Moving to the city centre	Eight measures for residential preferences	BE and SS[b]. Residents moving to the city centre reduced car use to work; residential choice was either conditional on or interacted with current commute mode choice for most respondents.
Handy and Clifton, 2001	1368 individuals and 75 interview participants in Austin, TX, 1995	Descriptive analysis and linear regression	Walking to store frequency	Miles to store, perceived store characteristics and neighbourhood dummy	Not available	BE and SS. Local store characteristics influenced walking frequency; but 'having the option to walk to the store is to some extent an effect of the desire to walk to the store'.
Statistical control						
Cao, Handy, *et al.*, 2006	1368 individuals in Austin, TX, 1995	Negative binomial regression	Strolling frequency and walking to store frequency	Objective and perceived neighbourhood characteristics, perceived store characteristics	Residential preference for stores within walking distance	BE and SS. Residential preference is the most important single factor explaining walking to store frequency; neighbourhood characteristics also had a separate influence on strolling frequency, while characteristics of local commercial areas had a separate influence on shopping trips.
Cao, Mokhtarian, *et al.*, 2006	1682 individuals from Northern California, CA, 2003	Nested logit model	Vehicle type choice	Objective and perceived neighbourhood characteristics	Various measures for residential preferences and travel attitudes	BE and SS. Attitudinal factors influenced vehicle type choice; BE also had a separate influence.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Cao *et al.*, 2005	1682 individuals from Northern California, CA, 2003	Seemingly unrelated regression	Frequencies of non-work trips by auto, transit and walking/biking	Objective and perceived neighbourhood characteristics	Various measures for residential preferences and travel attitudes	BE and SS. Residential self-selection is more likely to influence walking/biking trips than auto and transit trips; BE also had a separate influence on all trips.
Chatman, forthcoming[d]	999 adults in San Francisco and San Diego metro areas, CA, 2003	Negative binomial regression	Number of non-work activities accessed by auto, transit and walk/bike	Retail density, rail access, distance to downtown, number of four-way intersections, sidewalks, network load density	Preferences for auto, transit, walk/bike	BE > SS. Mode preferences affected non-work transit and walk/bike travel, but not auto; BE affected non-work transit and walk/bike travel after preferences included; impact of BE was independent of preferences.
Frank *et al.*, 2007[d]	2 sub-samples (n = 2056 and n = 1466) from the 2001–02 SMARTRAQ	Linear regression	Per cent of respondents taking walking trips, and vehicle miles travelled	Walkability index	Two factors of residential preferences	BE > SS for driving; BE and SS for walking. BE had an influence on walking and driving, controlling for residential preference; BE had a stronger influence on driving than residential preference, while the latter had a stronger influence on walking.
Kitamura *et al.*, 1997[d]	963 households in the San Francisco Bay Area, CA, 1993	Linear regression	Numbers of trips by non-motorized modes, transit and all modes; fractions of auto trips, transit trips and non-motorized trips	Residential density, land use mix and rail transit accessibility	Eight attitude factors	BE < SS. The residential environment had some influence on travel behaviour, but attitudes carried more explanatory power in explaining the variation in travel behaviour.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Schwanen and Mokhtarian, 2003[d]	1358 workers in the San Francisco Bay Area, CA, 1998	Ordered probit model	Respective trip frequencies for six purposes	Traditional and suburban neighbourhoods	Various measures for lifestyle, personality and travel attitudes; neighbourhood type mismatch (dissonance) indicators	BE > SS. BE exerted a significant influence on trip frequencies after SS controlled for, apparently more so on suburban dwellers than on urban residents.
Schwanen and Mokhtarian, 2005a[d]	1358 workers in the San Francisco Bay Area, CA, 1998	Multinomial logit model	Commute mode choice	Traditional and suburban neighbourhoods	Various measures for lifestyle, personality and travel attitudes; neighbourhood type mismatch (dissonance) indicators	BE > SS. Suburban-oriented urban dwellers were substantially more likely to commute by car than other urbanites, whereas urban-oriented suburban residents commuted by car at rates almost as high as other suburbanites. Thus, the separate influence of the BE, after controlling for SS, appears stronger in the suburbs.
Schwanen and Mokhtarian, 2005b[d]	1358 workers in the San Francisco Bay Area, CA, 1998	Tobit model	Respective distance travelled by auto, rail, bus, walking/jogging/biking and all modes	Traditional and suburban neighbourhoods	Various measures for lifestyle, personality, and travel attitudes; neighbourhood type mismatch (dissonance) indicators	BE > SS. Significant influence of the BE on distance travelled remained after SS was controlled for, with the BE influence stronger for suburban dwellers than for urban dwellers.
Instrumental variables models						
Boarnet and Sarmiento, 1998	769 Southern California, CA, residents, 1993	Instrumental regression	Non-work auto trip frequency	Density measures and street grid pattern at the block group/census tract and zip code levels	Not available	BE. BE at the neighbourhood level had little influence on non-work auto travel.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Greenwald and Boarnet, 2001	1091 individuals in the 1994 Household Activity and Travel Behavior Survey in Portland, OR	Instrumental regression	Non-work walking trip frequency	Density measures, street grid pattern and pedestrian environment factor at census block group, census tract and zip code levels	Not available	BE. The residential environment influenced non-work walking trip generation at the neighbourhood level.
Vance and Hedel, 2007	4328 individuals in the 1996–2003 German Mobility Panel	Instrumental regression	Car use and distance travelled	Commercial density, commercial diversity, street density and walking minutes to public transit	Not available	BE. All measurements but commercial diversity had a causal effect on travel behaviour.
Khattak and Rodriguez, 2005	453 households in Chapel Hill and Carrboro, NC	Binary choice model and negative binomial/ linear regression	Frequencies of auto trips, walking trips and external trips; distances for all trips and non-work trips; trip duration	Neo-traditional and suburban neighbourhoods	Eight measures for residential preference	BE. BE influenced most measures of travel behaviour.
Sample selection models						
Greenwald, 2003	4235 respondents in the 1994 Household Activity and Travel Behavior Survey in Portland, OR	Multinomial logit model and then linear regression	Eight substitution rates (walking/ driving and transit/ driving) for consumption, communication, socialization and all trips	Six groups based on housing tenure and three levels of pedestrian environment factor, and zone-based land use characteristics	Not available	BE. New urbanist designs increased walking substitution for driving, but had few effects on transit substitution for driving.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Zhou and Kockelman, forthcoming	1903 households in the 1998–99 Austin Travel Survey	Sample selection model	Vehicle miles travelled	CBD and urban vs. rural and suburban	Not available	BE > SS. Self-selection accounted for 10–42% of the total influence of BE on driving behaviour depending on model specifications.
Propensity score models						
Boer *et al.*, 2007	10 metropolitan areas in the 1995 NPTS	Propensity score matching	Choice of walking	Land use mix, density, housing age, block length, parking pressure and share of four-way intersections	Not available	BE and SS. A few influences from built environment elements remained after matching, but most became insignificant.
Cao, 2008[d]	1553 residents from Northern California, CA, 2003	Propensity score stratification	Vehicle miles driven, strolling frequency, walking to the store frequency	Traditional vs. suburban neighbourhoods	Various measures for residential preferences and travel attitudes	BE > SS. Self-selection accounts for 39% of the observed influence of neighbourhood type on walking to store frequency, 14% for strolling frequency and 22% for vehicle miles driven.
Simultaneous models						
Bagley and Mokhtarian, 2002[d]	515 individuals in the San Francisco Bay Area, CA, 1993	Structural equations model	Vehicle miles, transit miles and walk/bike miles	Two factor scores: traditional and suburban, based on various measures such as residential density and land use mix	Various lifestyle and attitude factor scores	BE < SS. Residential location type had little separate impact on travel behaviour; attitudes and lifestyles were the most important predictors of travel behaviour.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Bhat and Guo, 2007	2954 Alameda County households in the 2000 San Francisco Bay Area Travel Survey, CA	Joint nominal/ ordinal discrete choice model	Number of autos	Indicator of 233 TAZs, regional accessibility, density, land use traits and transportation network characteristics	Not available	BE; no SS. BE had true effects on auto ownership; no evidence of self-selection was found.
Cervero, 2007	11 369 workers in the 2000 San Francisco Bay Area Travel Survey, CA	Nested logit model	Rail commute choice	Residential location within or beyond half a mile of a rail station	Not available	BE and SS. Odds of commuting by rail ~40% higher for those living within 1/2-mile of rail station, compared to those living farther away.
Chen *et al.*, 2008	2089 commuters in the New York metropolitan region, 1997–98	Simultaneous equation	Car ownership	Density, job accessibility	Not available	BE and SS. The unobserved attitude towards using a car influenced car ownership; the built environment had a separate influence beyond the attitude and demographics.
Circella *et al.*, 2008	1217 workers from Northern California, CA, 2003	Structural equations model	Weekly miles driven	Perceived neighbourhood characteristics	Various measures for residential preferences and travel attitudes	BE and SS. Attitudes influenced both the choice of the built environment and driving behaviour; the latter two were also associated.
Pinjari *et al.*, 2007	1878 Alameda County commuters in the 2000 San Francisco Bay Area Travel Survey, CA	Joint nominal/ nominal discrete choice model	Commute mode choice	Indicator of 233 TAZs, regional accessibility, density, land use traits and transportation network characteristics	Not available	BE and SS. Self-selection resulted from observed and unobserved factors; BE had a separate effect on mode choice, after accounting for the influence of self-selection.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Salon, 2006[d]	4382 New York City respondents to the Regional Travel-HH Interview Survey	Nested logit model (residence choice, auto ownership, walking level)	Walking level (none, some, a lot)	Population density	Not available	BE > SS. Self-selection accounted for 1/3–1/2 the total influence of BE.
Scheiner and Holz-Rau, 2007	2691 residents in Cologne, Germany, 2002–03	Structural equations model	Mode use, vehicle kilometres travelled	Quality of transit, density of supply and density and mixed use	Lifestyle factors and attitudes towards residential choice	BE and SS. Attitudes influenced both the choice of BE and TB; the latter two were also associated.
Longitudinal designs						
Boarnet *et al.*, 2005	862 respondents to SR2S programme, CA, 2002	*t*-tests	Walking/biking to school	SR2S projects including sidewalk, crossing and traffic control improvements	Not available	BE. All improvements increased walking/biking to school for children.
Cao *et al.*, 2007a	1682 individuals from Northern California, CA, 2003	Linear regression (ordered probit model[c])	Number of autos; changes in number of autos	Objective neighbourhood characteristics; perceived neighbourhood characteristics and their changes	Various measures for residential preferences and travel attitudes	BE and SS. The cross-sectional analysis showed the influence of attitudes on auto ownership; the longitudinal analysis showed separate effects of BE.
Cao *et al.*, 2007b	547 movers from Northern California, CA, 2003	Structural equations model	Respective changes in driving, walking/biking and number of autos	Objective neighbourhood characteristics; perceived neighbourhood characteristics and their changes	Various measures for residential preferences and travel attitudes	BE and SS. Attitudes influenced auto ownership and travel behaviour; BE also had a separate effect.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
Handy *et al.*, 2005	1682 individuals from Northern California, CA, 2003	Ordered probit model (linear regression[c])	Vehicle miles driven per week; changes in driving	Objective neighbourhood characteristics; perceived neighbourhood characteristics and their changes	Various measures for residential preferences and travel attitudes	BE and SS. The cross-sectional analysis showed the influence of attitudes on driving distance; the longitudinal analysis showed separate effects of BE.
Handy *et al.*, 2006	1682 individuals from Northern California, CA, 2003	Ordered probit model (negative binomial regression[c])	Strolling frequency, walking to the store frequency; changes in walking and changes in biking	Objective neighbourhood characteristics; perceived neighbourhood characteristics and their changes	Various measures for residential preferences and travel attitudes	BE and SS. The cross-sectional analyses showed the influence of attitudes on walking behaviour; the longitudinal analyses showed separate effects of BE on walking and biking behaviour.
Krizek, 2000	549 households moving over the seven waves of the Puget Sound Transportation Panel, WA	Pairwise *t*-tests	Respective changes in trip distance, trip time, tour distance, tour time, trips per tour, and percentage of total trips by alternative modes	Changes in the Less Auto Development Urban Form (LADUF) index	Not available	BE. Individuals chose residential neighbourhoods partially to match their travel preference; moving to a different residential environment had little influence on travel behaviour given that only 9 out of 36 *t*-tests are significant.
Krizek, 2003a	6144 individuals over the seven waves of the Puget Sound Transportation Panel, WA	Linear regression	Respective changes in vehicle miles travelled, person miles travelled, number of tours and number of trips/tour	Respective changes in neighbourhood accessibility and regional accessibility at the residence and workplace	Not available	BE. Changes in neighbourhood accessibility and regional accessibility at the residence influenced most changes in travel behaviour; regional accessibility at the workplace affected some changes in travel behaviour.

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Table 1. (*Continued*)

Studies	Sample	Methodology	Travel behaviour measurements	Built environment measurements	Attitude measurements	Conclusions[a]
McBeth, 1999	The central area of Toronto, 1993–98	Descriptive analysis	Bicycle volume	Bicycle lane installations	Not available	BE. The installation of bicycle lane increased bicycle volume.
Meurs and Haaijer, 2001	189 movers and 524 non-movers participating in the Dutch Time Use Study in 1990 and in 1999	Linear regression	Respective changes in the number of trips by auto, bicycle, walking, transit and all modes	Respective changes in home characteristics, street characteristics and neighbourhood characteristics	Not available	BE. Individuals' travel behaviour was changed when moving to a different residential environment; non-movers' travel behaviour was also changed but not great when the environment was changed.
Painter, 1996	3 streets and a footpath, London	Descriptive analysis	Pedestrian volume after dark	Street light improvements	Not available	BE. Street light improvements increased pedestrian volume after dark.
Wells and Yang, 2008	70 low-income women in Florida, Alabama and Georgia collected from 2003–06	Linear regression	Weekly walking steps	Neighbourhood type, land use mix, street patterns, density	Not available	BE. The cross-sectional analysis did not show an association between neighbourhood type and walking; the longitudinal analysis found changes in land use mix and street patterns had influences on walking.

[a]The limitations discussed in the text should be kept in mind while reviewing these conclusions.
[b]BE means evidence found for the influence of the built environment on travel behaviour and SS means evidence found for the influence of residential self-selection on travel behaviour.
[c]Both a statistical control approach and a longitudinal design were adopted in these studies. The modelling technique in parentheses was used for the statistical control approach.
[d]These studies qualitatively explored which of BE and self-selection is more important. Among them, Cao (2008), Salon (2006) and Zhou and Kockelman (forthcoming) quantitatively presented their relative contribution.

Hammond (2005) studied the decision process relating residential choice (RC) and travel choice. In a self-administered survey, he first asked respondents living in Century Wharf, Cardiff (an isolated, compact and mid-size provincial city in the UK), to answer questions regarding RC and commute mode choice. He concluded that living in the city centre is associated with lower levels of auto use. In fact, living in the city centre and workplace proximity are the two most important reasons among others for lower car use. Respondents were also asked to describe their decision sequence. He found that 18% of the 90 respondents selected commute mode before making their decisions on residential location, and that 39% chose residence and commute mode simultaneously. This result indicates that for more than half of the sample, RC is either conditional on or interacts with commute mode choice. Through an eight-person focus group, he found that participants incorporated commute mode choice and access to work into their RC, and that all participants were commuting by the mode (including car, bus and train) that they had expected to use when looking for a residence (although one participant planned to change mode). Therefore, people selectively locate in a residential neighbourhood to realize their travel preferences. However, almost all of these results are not based on statistical tests but on descriptive analysis.

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Although the direct questioning approach may appear primitive next to more complex quantitative methods, it requires considerable ingenuity to execute well. Done well, it may offer valuable information regarding the process of residential and travel choices, sometimes beyond what multivariate analyses can do. It can also be used effectively in conjunction with quantitative approaches, for example in the development of survey instruments, the identification of appropriate model specifications and/or market segments having different decision-making processes and the validation of multivariate analyses (Pendyala, 1998; Clifton and Handy, 2003). Nevertheless, used on its own it has several limitations. First, the sample size is generally small and may not be representative of the population of interest (in part because the small size makes it more difficult to be representative, but also because people willing to engage in direct questioning of their behaviour may differ from the population at large in relevant ways, such as being less time-pressured, more self-confident, potentially more aggressive and so on). Moreover, direct questioning is likely to suffer from a number of biases, including memory, consistency, saliency (recency) and social desirability.[2] Equally importantly, direct questioning does not allow us to quantify the relative contributions of the BE and residential self-selection. In addition, this approach is vulnerable to most of the limitations pertaining to the other approaches.

Statistical Control

The method of statistical control explicitly accounts for the influences of attitudinal factors in analysing TB, by measuring them and including them in the TB equation (thereby moving them from unobserved to observed). This approach has been operationalized in two different ways in the literature.

Direct incorporation of attitudes. Using data collected from 999 adults in the San Francisco Bay Area and the San Diego metropolitan area in 2003, Chatman (forthcoming) studied the confounding influence of modal (auto, transit, walk/bike) preferences in the relationship between the BE and non-work travel. Through negative binomial regressions, he found that respondents who sought transit and walk/bike access (to shops/services and for all travel purposes) were more likely to conduct non-work travel by transit and walk/bike, respectively, but auto travel was not significantly influenced by auto access preference. After controlling for these attitudinal factors, he also found that proximity to heavy rail stations, retail density and distance to downtown had an influence on non-work travel by transit, and number of four-way intersections influenced walk/bike travel. Further, Chatman found that the effects of BE characteristics on TB showed few differences between those with strong and weak preferences. Chatman concluded that the residential self-selection problem is not a big concern, at least for his dataset.

Kitamura *et al.* (1997) incorporated attitudinal measures into the specification of linear regression models of TB, using survey responses from about 800 residents in five neighbourhoods in the San Francisco Bay Area in 1993. They first regressed socio-demographic and neighbourhood characteristics against frequency and share of trips by mode. Measurements of residential density, public transit accessibility, mixed land use and the presence of sidewalks were found to be significantly related to mode choice and trip generation by mode, controlling for socio-demographic characteristics. After attitudinal measures entered the model, they found that attitudes explain TB better than neighbourhood characteristics, which lends some support to the self-selection speculation. However, several BE characteristics (parking spaces available, distance to nearest bus stop and distance to nearest park) remained significant in the model for fraction of trips by auto.

Cao, Handy, *et al.* (2006) investigated the determinants of trip frequencies for strolling and walking to the store, using the same data as Handy and Clifton (2001). Two separate negative binomial models showed that although a preference for stores within walking distance impacts both types of trips, it is the most important factor explaining walking to the store among the variables tested. However, after controlling for self-selection, neighbourhood characteristics (especially perceptions) impact strolling frequency, while characteristics of local commercial areas are important in facilitating shopping trips. Similar to the previous one, this study indicates that residential self-selection at least partially contributes to differences in pedestrian behaviour, but that the BE does exert a separate influence beyond that. However, the single attitude measurement included may not have completely captured the influence of self-selection (e.g. a preference for recreational strolling was not measured). To the extent that unmeasured influences were at work, their models may overstate the influence of the BE.

To overcome this limitation, the same authors measured more than 12 dimensions of residential preferences and travel attitudes in a new research design. Using data collected from 1682 respondents in Northern California in 2003, Handy *et al.* (2005, 2006), Cao *et al.* (2005, 2007a) and Cao, Mokhtarian, *et al.* (2006) explored the influence of the BE and residential self-selection on driving behaviour, walking behaviour, non-work TB by various modes, vehicle type choice and auto ownership (AO) decisions, respectively. All studies conducted cross-sectional analyses, and some of these studies also adopted quasi-longitudinal designs (discussed in the ‘Longitudinal Designs’ section). In the cross-sectional analyses, the respective modelling techniques employed were linear regression, negative binomial regression, seemingly unrelated regression, nested logit and

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ordered probit. These studies measured the residential BE both subjectively, through factor analysis of respondents' perceptions, and objectively, through GIS analysis. After controlling for attitudinal and socio-demographic factors, Handy *et al.* (2006) found that both perceived neighbourhood characteristics and objective accessibility variables influence walking to the store frequency, and perceived aesthetic quality and social context of residential neighbourhoods affect strolling frequency. Cao *et al.* (2005) concluded that the BE has an influence on frequencies of non-work travel by auto and transit while attitudinal factors have an incremental contribution to explaining the variations in these behaviours, and both the BE and residential self-selection affect walking/biking non-work trip frequency. Cao, Mokhtarian, *et al.* (2006) found that vehicle type choice is greatly impacted by attitudinal factors, but commute distance and parking availability have a separate influence on the choice of SUVs and pickup trucks, respectively. By contrast, Handy *et al.* (2005) and Cao *et al.* (2007a) found that neighbourhood characteristics were displaced by preferences for the same aspects when modelling vehicle-miles driven and AO, suggesting that the observed associations with neighbourhood traits are a consequence of residential self-selection.

Comparison of consonant and dissonant residents. The second form of the statistical control approach is to compare the TB of residentially consonant and dissonant individuals. Here, in addition to incorporating travel-related attitudes into the equation for TB, attitudes towards residential location type are used to classify survey respondents as consonant (well-matched) or dissonant (poorly matched) with respect to their current residential location. The TB of dissonant residents is then compared to that of consonant residents in the type of neighbourhood in which they would rather live, and in their current neighbourhood. If the TB of dissonant residents is more similar to that of the consonant residents in their *desired* type of neighbourhood, it suggests that their predispositions dominate their TB. If their TB is more similar to that of the consonant residents in their *current* neighbourhood, it suggests that the BE exerts a separate influence that outweighs a contrary predisposition. Alternatively, a continuous measure of the degree of dissonance, as well as measures of the BE, can be incorporated into the TB equation, and tests performed to see whether the BE remains significant after dissonance is accounted for.

In three studies of a 1998 sample of 1358 residents of the San Francisco Bay Area, Schwanen and Mokhtarian compared the trip frequency (2003), commute mode choice (2005a) and mode-specific distances travelled (2005b) of dissonant suburban and urban residents (those who preferred a more or less, respectively, dense/diverse neighbourhood than the one they currently lived in) to their consonant counterparts in both kinds of neighbourhoods. In general, they found that while *suburban* residents' TB was similar whether they were consonant or dissonant, dissonant *urban* residents' behaviour fell between that of consonant urban and consonant suburban residents—more auto-oriented than the former but less so than the latter. These findings suggest that the BE does in fact play a role, at least in constraining and possibly in shaping, one's underlying preferences. Unfortunately for the goal of reducing auto dependence, the role does not appear to be symmetric, and the asymmetry is not in the societally desirable direction: urban-oriented suburban residents are less able to achieve their preference for non-auto travel than suburban-oriented urban dwellers are able to realize their preference for auto travel. However, in these studies too, residential

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preferences were captured with a single variable—attitude towards residential density/diversity. Although that attitude was a factor score representing a composite of several different elements (e.g. housing type, having shops and services within walking distance, and yard size), it still leaves room for improved measurement of residential preferences.

Frank *et al.* (2007) adopted both methods. They first incorporated residential preferences and a walkability index in linear regression models of TB. Then they classified the respondents into a 2×2 matrix (based on two binary variables of residential preference and walkability) indicating matched and mismatched residents, and compared their TB. They applied these techniques to two sub-samples drawn from the 2001–02 Strategies for Metropolitan Atlanta's Regional Transportation and Air Quality (SMARTRAQ) study. Overall, they found that both residential preference and BE characteristics affect walking and driving behaviour, with particularly the linear regression models for VMT suggesting a stronger BE influence. With respect to matched and mismatched residents, somewhat in contrast to Schwanen and Mokhtarian, they found that residents of high walkable areas drove similar amounts on average, regardless of their preferences, while residents of low walkable areas drove less if they preferred pedestrian-/transit-oriented neighbourhoods than if they preferred auto-oriented ones. Again, in each sub-sample, residential preference was represented by a single indicator, which is a composite measure of several dimensions of the preferences for the BE.

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Although the statistical control approach can offer insightful evidence of residential self-selection, it is vulnerable to several intrinsic limitations. First, attitudes are not straightforward to measure and analyse, and are often not measured, for example, not available in standard travel/activity diary data sets, and hence pose significant difficulty in the context of region-wide travel demand forecasting. Even when they *are* measured, they are measured with error, and may not comprehensively capture all the relevant attitudes. Second, when data are cross-sectional, there can be a temporal mismatch: the attitudes measured in the present may differ from those leading to the prior choice of the BE. Third, these studies modelled only a single causal direction, from the BE to TB. As illustrated in Figure 1, this is too simplistic a representation of the potential interactions among these variables.

Instrumental Variables Models

Another approach to address residential self-selection is to use instrumental variables (IVs) to purge BE of its correlation with ε. A time-honoured econometric technique, it involves (as applied in this context) first modelling BE as a function of relevant 'instruments', z, that are not correlated with the error term of the TB equation, and then replacing the observed BE in the TB equation with its predicted value $\widehat{BE}$ from the first-stage model.

Boarnet and Sarmiento (1998) employed ordered probit models to estimate non-work auto trip frequency, using 1993 data from 769 Southern California residents. Population density, retail employment density, service employment density and street grid patterns at the block group/census tract level and at the zip code level were chosen to measure the BE. They initially found that none of these variables were significant in the models. Then they chose four non-transportation neighbourhood traits as BE instruments: African American population share, Hispanic population share and percentages of housing built before

1940 and before 1960. After performing IV regressions, they found that the predicted BE variables became statistically significant in only one specification of the model. In particular, predicted service employment density became significant to non-work auto trip frequency when both employment densities at the zip code level were instrumented.

By contrast, Greenwald and Boarnet (2001) found a different pattern when modelling non-work walking frequency. Using 1091 individuals from the 1994 Household Activity and Travel Behavior Survey in Portland, Oregon, they employed ordered probit models to test walking frequency against BE variables and socio-demographic characteristics. They initially found that population density, retail employment density, street grid patterns and pedestrian environment factor (PEF) score were significantly associated with non-work walking frequency. Thereafter, they selected six variables as instruments: per capita income in the area (census block group only), percentage of population living in the geographical area with at least a college education, African American population share, Hispanic population share, share of housing that was rural but not farms and share of housing that was urban. After performing IV regressions, they showed that most predicted BE variables at the census block group and census tract levels remained significant while those at the zip code level became insignificant. Therefore, they concluded that the BE influences non-work walking trip generation at the neighbourhood level.

Using 4328 individuals (whose households have at least one car) in the 1996–2003 German Mobility Panel, Vance and Hedel (2007) investigated the effect of BE elements on car use (a binary variable) and distance travelled.[3] Following Boarnet and Sarmiento (1998), they chose four non-transportation variables as instruments: the respective percentages of buildings built before 1945 and between 1945 and 1985, the percentage of senior residents and the percentage of foreign residents. The results of IV models showed that commercial density, street density and walking time to public transportation had true effects on TB.

Instead of using instruments to model a continuous BE variable, Khattak and Rodriguez (2005) modelled a binary RC variable. Using 453 households from a neo-traditional neighbourhood in Chapel Hill and a suburban neighbourhood in Carrboro, North Carolina, they first developed a binary logit model for neighbourhood type choice (pseudo R^2 was 0.27), with residential attitudes as instruments. Then they incorporated the predicted probabilities of neo-traditional neighbourhood choice into three negative binomial regression models for auto trip frequency, external trip frequency and walking trip frequency, and two linear regression models for trip distance and trip duration. They concluded that households with high predicted probabilities of living in the suburban neighbourhood conducted more auto trips and external trips, walked less and travelled longer distances than those with high predicted probabilities of living in the neo-traditional neighbourhood. However, some if not all instruments that they selected for the RC equation may not be appropriate. Generally, IVs should satisfy two criteria: they must be highly correlated with the endogenous explanatory variable they are predicting (‘relevance’), but not be significantly correlated with the error term of the original equation (‘exogeneity’; Hall *et al.*, 1996; Cameron and Trivedi, 2005); in this case, the endogenous explanatory variable is neighbourhood choice and the error term reflects unmeasured attitudes. Although Khattak and Rodriguez explicitly stated that they excluded attitudes that are expected to be associated with TB and hence correlated with the error

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term in an equation for TB, they did not provide any empirical evidence of independence from TB for the attitudes they *did* include. To the contrary, other studies suggest that some of their instruments may be correlated with TB. For example, Cao, Handy, *et al.* (2006) and Handy *et al.* (2006) found that residential preference for stores within walking distance, a dimension similar to "having shops and services close by is important to me" in Khattak and Rodriguez (2005, p. 493), is significantly associated with walking frequency.

This discussion illustrates the intrinsic limitations of the IV technique (see e.g. Bound *et al.*, 1995). The problem is that BE or RC (in this context) must be *substantially* correlated with the error term for the TB equation in order for endogeneity bias to be a problem; small correlations between observed and unobserved variables are tolerated all the time, without remedial measures being required or taken. But in that case, first of all, finding suitably uncorrelated variables with which to model BE (i.e. meeting the exogeneity criterion) can be difficult. Second, modelling BE as a function of variables *uncorrelated* with the error term will therefore necessarily leave a sizable portion of the variance in BE unexplained (thereby falling short on the relevance criterion).

When the instruments explain very little about BE (a condition known as low relevance or 'weak instruments'), the coefficient in the second-stage equation of the resulting $\hat{BE}$ is a very poor estimator of the true impact of BE on TB. Under these circumstances, errors in either direction are quite possible: not only could $\hat{BE}$ appear insignificant in the equation for TB although the true influence of BE is non-zero, but also, conversely, $\hat{BE}$ could appear significant in the equation for TB, even when the true influence of BE is zero (Hall *et al.*, 1996). To judge whether this could be a problem, some measures of instrument relevance, such as the R^2 or pseudo-R^2, for the first-stage model should be reported; those measures are not available for at least three studies discussed earlier. Further, special account needs to be taken of the sampling variance in $\hat{BE}$, or else incorrect statistical inferences on the significance of its coefficient in the TB model may result.

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Sample Selection Models

Individuals observed to be living in a traditional neighbourhood are often different from those in a suburban neighbourhood. The basic idea behind sample selection models is to explicitly model the prior selection into different discrete states (residential location types here)—the 'participation' or 'selection' equation—and model the outcome of interest (TB) as conditional on that prior selection—the 'outcome' equation. This approach is an extension of Heckman's selection model (Heckman, 1976; Heckman *et al.*, 2001).

Greenwald (2003) used a multinomial logit participation equation following Lee (1983). In particular, he classified 4235 respondents from the 1994 Household Activity and Travel Behavior Survey in Portland, Oregon, into six types of residential conditions based on residential tenure (own, rent) and three levels of the PEF score. A multinomial logit model was developed to predict individuals' RC (pseudo-R^2 was 0.33). Then, he inserted the predicted probability of the *observed* RC into eight separate models of 'substitution rates', intended to represent travel time choices for a 'typical' trip in each category. He found that the predicted probability significantly (negatively) influenced the ratio of median transit time to median driving time, for consumption and socialization purposes, as well as in the model for all trips. After accounting for the influence of residential self-selection in this way, he also found that some BE variables were significant in all models.

However, Greenwald's specification departs from the classic formulation of a selectivity model. First, in a two-stage selectivity model, the new explanatory variable in the outcome equation is not the predicted participation probability but the inverse Mills ratio (IMR: for simplicity, if the participation equation is a binary probit model, the IMR = $\phi(\beta' X)/\Phi(\beta' X)$, where ϕ and Φ are the probability density function and cumulative density function of a standard normal distribution, respectively) derived from the participation equation (Lee, 1983; Cameron and Trivedi, 2005). Second, in a multinomial logit-OLS model, the number of outcome equations is not one but depends on the number of alternatives in the multinomial logit model (Lee, 1983). It is problematic to interpret the impact of the estimated probability of the single *chosen* residential alternative (which could be any of the six types, whether more or less pedestrian-oriented) on the travel time ratio (substitution rate): interpreted directly, the model indicates that the better RC is predicted (i.e. the higher the predicted probability of the chosen residential location type)—no matter what that choice may be—the higher median driving trip time tends to be, compared to median transit trip time. Therefore, the ability of this model to correct for selectivity bias is unclear.

Zhou and Kockelman (forthcoming) pioneered the application of the sample selection model to determine the relative contributions of the BE and self-selection to TB. Specifically, they classified 1903 households in the 1998–99 Austin Travel Survey into two groups: CBD and urban residents (control), and rural and suburban residents (treatment). They first modelled the prior RC (pseudo-R^2 was 0.07) and then inserted a derived lambda (which is the IMR for the treatment group and $\phi(\beta' X)/[1-\Phi(\beta' X)]$ for the control group) into the two equations for VMT of the treatment and control groups. They calculated and compared the average treatment effect (ATE: the average increase in VMT of moving a *randomly selected person* from an urban neighbourhood to a suburban one, or the *true* influence of the BE) and the effect of treatment on the treated (TT: the average increase in VMT of having moved a *randomly selected suburban resident* from an urban neighbourhood to a suburban one, or the *total* influence of the BE) (Heckman *et al.*, 2001). They found that self-selection (the difference between TT and ATE) accounted for 10–42% of the total influence of the BE on TB, depending on model specifications. In their outcome equations, however, they included population density and job density besides demographics and lambda. The appropriateness of including these BE variables is debatable. The type of the residential neighbourhood is a result of self-selection. So are BE elements associated with the neighbourhood. For example, those who are observed to be living in high density (or accessibility) areas may differ from those in low density (or accessibility) areas. Therefore, these variables could still be correlated with unobserved characteristics influencing TB, in violation of the model's assumption. Further, although there appears to be little discussion in the literature on the efficacy of the participation equation (i.e. its 'relevance', to borrow the IV terminology), the low pseudo-R^2 of that equation in this application is cause for concern (Ed Vytlacil, personal communication with Cao, 30 May 2008), analogous to the problem of weak instruments in the IV model.

Although Heckman's sample selection model is valuable for separating various types of treatment effects (Heckman *et al.*, 2001), its model specification precludes the inclusion of other BE variables in TB equations because of their endogenous

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nature as discussed earlier. This challenge is not insurmountable. For example, as Greenwald (2003) did, we can classify residents into groups along a few dimensions of the BE and then apply a multinomial logit model for RC (Lee, 1983). In this case, the model involves multiple treatments, and generalized point estimates for those treatment effects are needed.

Propensity Score

The propensity score method is highly recommended in social epidemiology (Oakes and Johnson, 2006).[4] In a non-randomized observational study, treatment is a result of self-selection. A direct comparison of outcomes (TB) between those in treatment and control groups (traditional vs. suburban neighbourhoods) tends to produce biased treatment effects because individuals in these two groups may have systematic differences on some characteristics. Alternatively, we can mimic a randomized experiment using a propensity score. The propensity score is the conditional probability that an individual receives a treatment given a set of observed covariates (Rosenbaum and Rubin, 1983). Simply put, the propensity score is the predicted probability of a binary choice model in which the dependent variable is the decision to receive a treatment and personal characteristics are independent variables. In practice, the propensity score has been used to address the non-random assignment of treatment through such applications as stratification, matching and regression (covariance) adjustment (Rosenbaum and Rubin, 1983; D'Agostino, 1998).

In *regression adjustment*, the propensity score enters the TB equation as a new independent variable. Therefore, the Khattak and Rodriguez (2005) study discussed earlier is more or less an application of propensity score regression adjustment. In *propensity score matching*, once we know the propensity score of a random individual in the treatment group, we can match this individual with a person who has the same propensity score (or within a predefined range) in the control group. Because both individuals have the same propensity score, this matching reduces the bias and hence produces balance in those personal characteristics. This approach mimics an experimental design in which two exchangeable individuals are randomly assigned to the treatment group and the control group. Once the matching is complete, the ATE is the difference in the mean outcomes between those in the treatment and control groups. *Propensity score stratification* classifies respondents into several groups based on the predicted probability, and then compares the mean outcomes in each stratum. The ATE for the whole sample is an average of the differences in the mean outcomes. This approach mimics an experimental design for each stratum (Rosenbaum and Rubin, 1983, 1984).

The propensity score method is different from statistical control (see the 'Statistical Control' section). Conceptually, the propensity score method controls for the observed characteristics that affect *whether an individual is assigned to a treatment group or a control group*. The attention is directed to the imbalance in the values of covariates between treatment and control groups. The statistical control method *identifies the determinants of TB* through incorporating them directly into the behaviour equation, so that we can account for all differences between treatment and control groups that affect the behaviour. The attention is directed to the behavioural outcome (Winship and Morgan, 1999; Oakes and Johnson, 2006). In reality, however, when the propensity score is used as a regressor in the outcome

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equation, it is acting as one type of statistical control, namely a composite of the variables differentiating the treatment and control conditions. Empirically, the model used to estimate a propensity score is a prediction model so it is not necessary to evaluate multi-colinearity and statistical significance of explanatory variables; interaction and polynomial terms are always encouraged for propensity score estimation (Oakes and Johnson, 2006). However, multi-colinearity and statistical significance are important for an explanatory model in the statistical control approach.

The sample selection model for a binary endogenous variable is essentially a generalized propensity score approach, although the application of the former is earlier than that of the latter (Winship and Morgan, 1999). The difference between the two approaches is that the sample selection model requires a strong normality assumption and inserts a lambda into the behaviour equation, but the application of a propensity score as a regressor inserts the estimated probability into the behaviour equation (Winship and Morgan, 1999).

The propensity score approach has recently been applied in the field of TB. Boer *et al.* (2007) explored the influence of BE elements on walking choice (binary), using the US 1995 National Personal Transportation Survey (NPTS). Their logistic regression propensity model included individual and household traits as regressors. The goodness of fit of the model was not provided. Without the propensity score matching, they found that land use mix, density and parking pressure (defined as number of residents per foot of parkable street length) were significantly associated with walking choice. With the matching, many previously significant relationships became insignificant. Therefore, self-selection played an important role in walking choice.

Using 1553 residents in Northern California, Cao (2008) applied propensity score stratification to estimate the true effect of neighbourhood type on TB. He developed a binary probit model for RC (traditional and suburban neighbourhoods), with demographics, residential preferences and travel attitudes as independent variables. Then he classified these residents into quintiles based on the propensity score and calculated the ATEs of neighbourhood type. The results showed that, on average, the true effect of neighbourhood type on driving distance is 18.0 miles per week, which accounts for 12% of individuals' overall vehicle-miles driven. The ATE on walking to store frequency is 1.86 trips per month, which accounts for 61% of the observed difference. The ATE of neighbourhood type on strolling frequency is 2.05 trips per month, which accounts for 86% of the observed difference. Therefore, neighbourhood type has a more important influence than self-selection.

The propensity score method has many limitations (Oakes and Johnson, 2006). Because the computation of propensity score relies on observed characteristics, the method does not consider any bias due to unobserved characteristics. Thus, if unmeasured attitudes are a source of self-selection, this approach cannot compensate for that. Also, the approach can be employed only if there is a large amount of overlap in the scores for those in the treatment and control groups. Otherwise, for matching, one may not be able to find many matched pairs and most information in the data will be lost. Excluding the unmatched cases in the treatment group is likely to discard important information about the types of people selecting treatment, and the outcomes for those types, biasing the sample (and the resulting coefficient estimates) in a different way. For stratification, few overlaps in the propensity score may yield only few observations in either treatment or

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control group and hence make comparison impossible. The matching may be sensitive to the predefined calliper-width (i.e. range for determining whether or not two observations are matched). If the width is too small, one may not be able to find a match for many individuals in the treatment group; if the width is too large, the ability to reduce bias is limited. Finally, the propensity score approach is commonly used for a binary (yes–no) treatment variable. There is some extension to multiple treatment conditions, but the usefulness of the extension is unclear (Oakes and Johnson, 2006).

Other Joint Models

Instrumental variable and sample selection models contrast to single-equation statistical control models in that the former try to jointly account for multiple endogenous choices—residential location and TB in this case. Three other types of models that simultaneously account for multiple choices appear in the literature: joint discrete choice models involving nominal and/or ordinal endogenous variables, structural equations models (SEMs) involving continuous endogenous variables and mutually dependent discrete choice models. These models have recently become very popular, as shown by the number of studies published since 2006 alone. We discuss each in turn.

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Joint discrete choice models. In *joint discrete choice models*, the observed endogenous variables measuring RC and TB are both discrete, and the joint probability of an (RC, TB) bundle being chosen is modelled. This category can be further subdivided into two: 'sequential' and 'simultaneous' models. The *sequential* approach is represented by the multidimensional nested logit model (Ben-Akiva and Lerman, 1985), where both choices are treated as nominal, and in which one choice (most naturally, TB) is conditioned on the other (RC) so that the joint probability of an (RC, TB) bundle being chosen is modelled as Pr[RC] Pr[TB | RC]. Although nested logit models do not *impose* a sequential structure on multiple decisions (Sobel, 1980), they can certainly *reflect* one when it exists. The present context is one such natural application, since RC has long and widely been held (e.g. Salomon and Ben-Akiva, 1983) to be a longer-term choice which is antecedent to short-term choices related to individual trips. But it must be emphasized that finding such a structure to fit the data well cannot be taken as *confirmation* of a sequential decision process, only as being *consistent* with it. Further, analysts should not let a presumed temporal sequence of decisions blind them to alternative possibilities such as those shown in Figure 1.

Although a number of nested logit models incorporating residential location and TB have been developed (e.g. Abraham and Hunt, 1997), at least two have employed the technique explicitly to account for residential self-selection. Cervero (2007) developed a two-level nested logit model, with the upper level indicating the binary choice of residential location (whether or not to live within half a mile of a rail station) and the lower level representing the binary choice of commute mode (rail or auto). Using 11 369 workers in the 2000 San Francisco Bay Area Travel Survey (BATS), he calibrated the model, and then compared the average odds of choosing rail over auto for those living near rail stations (0.1547/0.8453 = 0.1830) to the average odds for those living farther away (0.1144/0.8856 = 0.1292). Cervero (2007, p. 2082) concluded that "the odds of rail commuting are 41.6% [the percentage by which 0.1830 exceeds 0.1292] greater if one lives near versus away from transit, all else being equal …. This suggests that around 40% of the higher rail commuting shares among Bay Area workers living near transit is accounted for by self-selection". However, we have two main concerns about this result. The first is that the odds ratio is not necessarily a percentage of a whole (i.e. mathematically, it could exceed 100%), and we do not see a logical translation from the factor by which the odds change, to a percent of commuting shares accounted for by residential self-selection. The second concern is that it is not clear how the *conditional* probabilities (e.g. Pr[TB = rail | RC = close to transit]) account for prior self-selection, as opposed to the direct influence of the BE (i.e. the fact that rail by definition is more convenient for those living closer to stations) once a residential selection has been made.

Using travel diary data from the Regional Travel–Household Interview Survey, Salon (2006) estimated a three-tiered nested logit model of RC (census tract), AO and walking level (WL) for 4382 residents of New York City. Given the available variables, she used population density as an indicator of neighbourhood walkability. Using the full joint model, she then computed various elasticities of WL with respect to population density (BE, for the sake of argument). She suggested that the effect of locational self-selection can be quantified by taking the difference between unconditional elasticities of WL and those computed to be conditional on RC. That is, the self-selection effect is the difference between (1) the elasticity of WL with respect to population density calculated from the marginal Pr[WL], and (2) those calculated from the conditional Pr[WL | RC]. With the application of this approach, Salon concluded that self-selection accounted for one-third to one-half of the effect of a change in population density (BE) on WL (TB) in most areas of New York City.

In the *simultaneous* joint discrete choice model, latent utilities for each choice, *RC** and *TB** are formulated in separate equations, with the probability of a particular (RC, TB) bundle being estimated jointly. The separate utility equations may have overlapping sets of explanatory variables, but (together with the other joint models discussed so far) do not include one endogenous variable directly in the equation for the other. Bhat and Guo (2007) pioneered the theoretical development and empirical application of such a joint structure modelling discrete RC and ordinal car ownership, parameterizing the error terms as follows:

$$\begin{aligned} RC^* &= b(BE, Z, X) + u\,BE \pm w\,BE + \varsigma \\ TB^* &= t\,(BE, Y, X) + \nu\,BE + w\,BE + \delta \end{aligned} \tag{2}$$

where u and v are unobserved (individual-specific) factors (such as attitudes) impacting households' sensitivity to BE traits in RC alone and travel choice alone, respectively; w stands for unobserved individual factors impacting both residential and travel choices;[5] and ζ and δ are idiosyncratic terms. By including the common error term $w\,BE$, Bhat and Guo's model simultaneously corrects for the endogeneity of the BE.

Using data from 2954 Alameda County households in the 2000 BATS, they calibrated this joint mixed multinomial logit-ordered response model. In their operationalization, RC is measured as a discrete indicator of one of 233 transport analysis zones; BE variables include measures for zonal density, zonal land-use structure, regional accessibility, local transportation network and commute-related variables; and TB is the ordinal measure of number of vehicles owned by the household. Their results showed that the lack of a significant common error

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term (more precisely, estimates of the variance of *w* that did not significantly differ from zero) failed to support the speculation that attitude-based self-selection influences AO choice. Although their initial application did not have observed attitudinal variables, the inclusion of such variables in future applications could provide additional insight into the sources of the relationship between the two choices: it is possible that the *w BE* terms in their system were insignificant because the correlation of the error terms for the two choices was due to unmeasured variables such as attitudes towards walking and/or driving rather than the BE variables that *were* measured.

Pinjari *et al.* (2007) extended Bhat and Guo's approach to incorporate a multinomial mode choice representation of TB. Using 1878 commuters from the same survey, they developed a joint model for residential location choice and commute mode choice. They found that the effect of self-selection results from both observed variables and unobserved factors, and the BE has an independent influence on mode choice beyond the influence of self-selection. Potential limitations of this extension are similar to those of Bhat and Guo (2007). Further, as elaborated ahead, these joint discrete choice models do not represent direct causal relationships between the endogenous variables of the system, only correlated error terms.

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Structural equations models. The second category of joint models is SEMs. By contrast to the joint discrete choice models, here the endogenous variables are typically continuous (potentially a shortcoming, in some applications), and they are usually modelled as directly influencing other endogenous variables. Such a model can explicitly recognize that not only do attitudes perhaps influence both BE and TB, but over time (as shown in Figure 1), both the BE and TB may affect attitude as well, and attitude and TB could affect BE (bringing about a residential relocation).

Using 1993 data on 515 individuals in the San Francisco Bay Area, Bagley and Mokhtarian (2002) employed SEM to investigate the relationships among the BE, TB and attitudes. Nine endogenous variables were incorporated into the structural model specification: two continuous residential type measures, three measures of travel demand, three measures of attitudes and one measure of job location. The exogenous variables consisted of socio-demographic characteristics, lifestyle factor scores and other measurements of attitudes. They found that with respect to direct and total effects, attitudinal and lifestyle variables had the greatest impact on travel demand among all explanatory variables, while residential location type had little separate influence on TB. These results lend strong support to the speculation that the observed relationships between the BE and TB are not direct causal links, but are primarily attributed to interactions of these measures with other variables.

Using a sample of 1217 workers collected from Northern California in 2003, Circella *et al.* (2008) explored the connections among six groups of variables: socio-demographics, travel attitudes, land use preferences, neighbourhood characteristics, AO and vehicle-miles driven. They treated the former two groups as exogenous variables and the remaining as endogenous variables. They found that travel attitudes and land use preferences were associated with neighbourhood characteristics and driving behaviour, and neighbourhood characteristics had an impact on driving behaviour. Therefore, they concluded the concurrent influences of the BE and residential self-selection on TB.

Scheiner and Holz-Rau (2007) applied SEM to a sample of 2691 residents in the region of Cologne, Germany, in 2002 and 2003. In this study, they investigated the interactions among life situation (socio-demographics), lifestyle factors, residential location attitudes, urban form and TB, with the latter four groups being endogenous variables. TB variables include mode use (the share of trips by a specific mode) and vehicle kilometres travelled. Quality of public transportation, density of supply (retail, service and leisure opportunities), and density and mixed use were chosen as the measurements of urban form. They developed eight SEMs with different model specifications. They found that individuals who prefer high quality of transit, good access to retail and service, and urban life were more likely to live in urban areas with high density and mixed use, and those living in such neighbourhoods tended to drive less and use alternative modes more. So both the BE and self-selection have influences on TB.

However, although allowing multiple directions of causality arguably constitutes a conceptual improvement over the single-equation and joint (simultaneous) model methodologies, the use of cross-sectional data is still a practical drawback to this approach. The same temporal mismatch between attitudes and BE described in connection with the statistical control models of the 'Statistical Control' section may occur here.

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Mutually dependent discrete choice models. The joint discrete choice models discussed earlier do not allow direct causality between their endogenous variables. By contrast, the SEMs of the preceding section are built around the concept of direct (potentially mutual) causality among endogenous variables, but in most TB applications to date, those variables are continuous. One recent application, however, conceptually blends both these approaches, jointly modelling discrete endogenous variables as mutually dependent.[6]

Chen *et al.* (2008) constructed two simultaneous equations, in which car ownership level and the propensity to use a car influence each other. In this specification, car use for commute trips (a binary variable) is observed but the underlying propensity to use a car is unobserved. Thus, this latent propensity is presumed by the authors to include unobserved attitudes towards car use. If residential self-selection is at work, it is expected that the propensity will have a significant impact on car ownership level. Chen *et al.* (2008) applied a two-stage estimation method to a sample of 2089 commuters (having cars in the household) in the New York metropolitan region. In particular, they first estimated a probit model for car use as a function of car ownership, demographics, BE variables and tour complexity (pseudo-R^2 was 0.60). They then inserted the predicted probability of using a car into an ordered probit model for car ownership. They found that car ownership level was not significant in the model for car use, but the predicted probability had a significant influence on car ownership level. Population density and transit-based job accessibility at home also had an association with car ownership.

The fact that the causality appeared to go only in one direction (car use propensity influencing car ownership level) in this application suggests that, empirically, this model could be viewed as an example of several other methods discussed earlier, and accordingly subject to their limitations. Specifically, the probit model of car use could be viewed as a propensity score model, where the predicted propensity (probability) is then included as a regressor in the outcome (car ownership) equation. As such, as mentioned in the 'Propensity Score Matching' section it is not clear how a propensity that is estimated as a function of observed characteristics can resolve an endogeneity bias caused by the correlation of observed with unobserved characteristics. The predicted car use probability is also related to, and serves a role similar to, that of the lambda term in the outcome equation of a sample selection model (although the lambda term is derived from theoretical considerations). As such, the concern we expressed with respect to the Zhou and Kockelman (forthcoming) study in the 'Sample Selection Models' section similarly applies here: inclusion of BE terms in the outcome equation may also be perpetuating an endogeneity bias.

Temporal mismatch is also an issue with this type of model; for example, present car use (or even the propensity to use a car, based on current variables) would not logically be expected to influence previously determined car ownership levels. Finally, the two-stage estimation approach is cause for concern. Had car ownership been significant in the equation for car use, and given that the converse was found to be true, it would be a clear case of simultaneity bias. That is, car ownership in the first equation would have been correlated with the error term of that equation, because, according to the second equation, car ownership is a function of car use, which includes the error term of the car use equation. This simultaneity of causality means that the coefficients of explanatory variables in the first-stage model would have been biased and inconsistent, rendering suspect the results of the second-stage model.

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Longitudinal Designs

A longitudinal design can be used to control for attitudes (and any other variables) that do not change over time. Therefore, studies using longitudinal designs implicitly or explicitly address (at least partially) the confounding influence of self-selection in the connection between the BE and TB. The situations to which this approach has been applied include residential moves, as well as changes 'in place' to the BE, for example, the 'Safe Route to Schools' (SR2S) programme.

In contrast to the disaggregate studies that underlie the rest of this paper, some studies have used a before-after design to investigate the influence of a specific change to the BE on aggregate TB. For example, Painter (1996) found that street light improvements in three urban streets and on a pedestrian footpath (previously prone to crime) in London greatly increased pedestrian street use after dark. McBeth (1999) concluded that installation of bike lanes in downtown Toronto increased bike volume. An advantage of these studies is that they concentrated on the observed changes in TB of people exposed to the study areas, rather than reported changes. However, they did not employ control locations or control for other variables. The lack of controls may confound the intervention effects with other potential effects. Further, with only aggregate measures of travel demand, it cannot be determined how the changes are distributed: are the same people using the facility more, are more people using it, or both? This question can be answered with true disaggregate panel data.

In an evaluation of California SR2S projects, Boarnet *et al.* (2005) examined the relationship between improvements in walking and biking infrastructures and children's walking and bicycle travel to school, based on retrospective responses of 1244 parents. Changes in these infrastructures (sidewalks, crossings and traffic control) serve as a 'treatment' for the children who passed the SR2S projects on their way to school (experimental group). The control group consists of those who did not pass the SR2S projects. Through paired-sample *t*-tests, they found that

15.4% of the 486 children who passed the SR2S projects increased their walking or bicycle travel to school, while only 4.3% of the 376 children who did not pass the projects increased their non-motorized travel. However, memory biases and social desirability biases (given that the 'desirable' answer was probably especially apparent to the treatment respondents) may be concerns of this study.

Krizek (2000) examined the changes in households' TB before and after their residential relocation, using the Puget Sound Transportation Panel data. Households' residential relocation may expose them to different BEs, serving as a 'treatment'. Households' TB was measured by a variety of variables, including trip distance, trip minutes, tour distance, tour minutes, trips per tour and percentage of total trips taken by alternative modes. Paired-sample *t*-tests were conducted to examine the changes in households' TB against the changes in the BE. The results showed relatively weak correlations between changes in the BE and changes in TB. He also found that more than half of his sample moved to a neighbourhood whose environmental characteristics were similar to their previous neighbourhood. This result suggests that households may decide to live in a neighbourhood at least partly to match their travel preferences. However, this study is vulnerable to a lack of control for other determinants of TB change.

Using the same dataset, Krizek (2003a) applied linear regression models to test whether changes in TB can be attributed to changes in neighbourhood accessibility, controlling for changes in socio-demographic characteristics, workplace accessibility and regional accessibility. TB variables used in this study are VMT, person miles travelled, number of tours and number of trips per tour. The results showed that the changes in neighbourhood accessibility are statistically significant in all models, which suggests that when households' neighbourhood accessibility changes, their TB also changes, all else being equal. The author pointed out, however, that the results should be interpreted with caution, as the changes in both neighbourhood accessibility and TB may be the result of changes in attitudinal predispositions towards the residential environment and travel choices.

Meurs and Haaijer (2001) investigated the extent to which changes in residential environment characteristics led to changes in travel patterns, using Dutch Time Use Study data from 1990 and 1999. For the dynamic analysis, the respondents were divided into two segments: movers and non-movers. Regression analyses were conducted on both segments, in which changes in the number of trips by various modes were regressed against changes in residential environment and personal characteristics. For the people who moved, changes in residential environment characteristics influence TB, and changes in employment and AO as well as other socio-demographic factors greatly influence changes in auto trip frequency. For the people who did not move, the observed effects of spatial changes (which were relatively minor and incremental, such as an extra garage and the provision of a bike path) are limited, as they expected. However, although the authors controlled for major socio-demographic determinants of mobility such as "family composition, work or activities, education, car ownership, etc." (Meurs and Haaijer, 2001, p. 434), the nine-year span between waves means that the age distribution of respondents in the study will be biased upward by the end. Further, it appears that non-movers were primarily analysed separately from movers, rather than explicitly used as controls.

Similarly, Cao, Handy, and Mokhtarian classified their Northern California respondents into movers and non-movers, based on whether they moved within the last year. They measured changes in the BE by taking the differences between

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movers' perceptions of current and previous neighbourhoods, and assumed the residential environment of non-movers to remain constant over the measurement period. Changes in TB were measured using a series of general indicators of the use of different modes compared to previously, on a five-point scale ranging from 'a lot less now' to 'a lot more now'. Residential preferences and travel attitudes were measured at only one point in time: currently. For these reasons, they refer to this design as 'quasi-longitudinal'. Handy *et al.* (2005, 2006) developed three ordered probit models to investigate whether changes in the BE influence changes in driving, walking and biking. After controlling for current attitudes and changes in socio-demographics, they found that for all respondents, changes in neighbourhood characteristics consistently affect changes in these behaviours, and changes in neighbourhood characteristics are the most important in explaining changes in driving and walking. Using linear regression, Cao *et al.* (2007a) found that for movers, a change in the perceived outdoor spaciousness of their neighbourhood impacts change in AO, and its influence is equivalent to that of socio-demographics.

This finding raises a concern that changes in AO may be endogenous to the associations between changes in the BE and TB. Accordingly, Cao *et al.* (2007b) employed a structural equations modelling approach to explore the complex relationships among endogenous variables, namely changes in the BE, AO and TB. They assumed that current attitudes and changes in socio-demographics affect changes in the BE, which in turn influence changes in AO and TB, and the latter two changes impact each other. They found that changes in neighbourhood characteristics have a true influence on changes in driving and walking. However, the latter two studies lack a control group of non-movers due to a survey design limitation. Although the dynamic structural equations modelling approach adopted in this study is an improvement in terms of methodology, there are still limitations in its application. Because it is not feasible to retrospectively measure attitudes, they have data on current attitudes only. So, they cannot rule out the competing hypothesis that an attitude change preceded and (partly) prompted the residential location change. To the extent that is true, the attitude change is confounded with the change in BE and may account for some of the apparent effect of the BE seen in this study.

Recently, Wells and Yang (2008) analysed cross-sectional data (70 low-income women in Florida, Alabama and Georgia) and longitudinal data (32 women) collected from 2003 to 2006. They employed linear regression modelling. The results of the cross-sectional analysis showed that there is no significant association between neighbourhood type and post-move walking. By contrast, the longitudinal analysis demonstrated that changes in the number of cul-de-sacs and changes in the number of service jobs per resident are negatively associated with post-move walking. Further, these two variables explained 16% of the variation in walking, in addition to 44% of variation being explained by pre-move walking and demographics. For the longitudinal analysis, they took advantage of a natural experiment, a critical approach in the field of neighbourhood design and physical activity (Oakes, 2004). These low-income women moved to either a neo-traditional community or a suburban neighbourhood, with the help from a housing programme. The women did not have an alternative choice because only one type of neighbourhood was available in each region. However, some women may opt out of this programme because they cannot afford a car, which may be necessary to live in a suburban neighbourhood. Therefore, although this study represents

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the commendable use of an unusual and valuable opportunity, the extent to which it is a true natural experiment is debatable. Also, of course, a sample size larger than 32 would be desirable.

Overall, longitudinal designs can offer substantial improvement over cross-sectional designs, providing a more robust causal inference on the relationship between the BE and TB. Longitudinal designs still have a number of limitations, however, both inherently and in the way they are likely to be applied in the present context: the required assumption of stability of the causal processes over time; the difficulty in achieving optimal spacing of measurements; self-selection into participation groups; and the added time and expense of data collection. Applications to date have been further hampered by not measuring attitudes across time and by not including feedback loops from the BE to attitudes.

Conclusions and Recommendations

The issue of causality—specifically, to what extent does the BE have a separate effect on TB after the influence of attitudinal predispositions has been properly accounted for?—has become one of the key questions in the debate over the link between the BE and TB (TRB-IOM, 2005). This paper identified nine approaches used in previous research to empirically address the issue of residential self-selection, and reviewed the empirical findings of 38 studies using those approaches.

In brief, research using the direct questioning method qualitatively found some evidence for residential self-selection (Table 1). Studies using the statistical control approach consistently found a pervasive confounding influence of self-selection in the association between the BE and TB, and most studies also found that the BE has a separate influence on TB (e.g. Kitamura *et al.*, 1997; Cao, Handy, *et al.*, 2006). IVs regression and sample selection models found evidence (strong in some studies; weak in others) that the BE had an impact after controlling for self-selection. Nested logit applications (Salon, 2006) report a sizeable influence of self-selection on TB, with the BE sustaining a direct influence beyond that. Two studies using propensity score found a true influence of the BE. With respect to the joint discrete choice model, Bhat and Guo (2007) found no influence of self-selection due to unmeasured variables such as attitudes, but its extension concluded an influence of both the BE and self-selection (Pinjari *et al.*, 2007). The studies adopting a structural equations modelling approach (e.g. Bagley and Mokhtarian, 2002; Cao *et al.*, 2007b) found an influence of residential selection, although the influence of the BE appeared to be stronger than that of self-selection in the latter study. Investigations employing a longitudinal design tended to support the argument that the BE has a causal influence on TB, although they acknowledged the potential influence of attitudinal factors.

In sum then, if the key question is, 'Does the BE have a distinct influence on TB after self-selection is accounted for?', then based on the empirical evidence to date, the answer would have to be a simple and resounding 'yes'. Virtually every quantitative study reviewed here, after controlling for self-selection through the various ways discussed earlier, identified a statistically significant influence of one or more BE measures on the TB variable of interest. Finding both a self-selection effect and a direct impact of the environment on behaviour is not surprising. People choose places to live based on a variety of factors including travel preferences. At the same time, environments vary in the degree to which they support

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different modes: it is easier, safer and nicer to walk in some environments than others. Once a walking-oriented person moves to a walking-oriented environment, we would expect her to walk more. But it is also good to know, from a policy standpoint, that when an auto-oriented person moves to a walking-oriented environment, we can expect her to walk somewhat more as well.

It is more difficult, however, to assess the strength of the autonomous influence of the BE relative to the influence of self-selection, or even to ascertain whether that autonomous influence is 'large enough to matter' on its own terms. Only ten of the studies (those marked with superscript 'd' in Table 1) indicated even qualitatively which of the two factors was stronger, and only three of those attempted to quantify the relative contributions of each. The BE had the stronger impact in eight of those ten studies, and among the three where relative contributions were quantified, the BE's proportion of the total combined effect ranged from 52% (Salon, 2006, taking the results for New York City as a whole) to 90% (Zhou and Kockelman, forthcoming). But in view of the large number of studies that were silent on this question, it would be unwise to draw definitive conclusions on the relative influence of the BE from these findings.

In general, ironically, it seems as though the more sophisticated the approach to treating self-selection (and therefore, presumably, the more trustworthy the resulting effects that are identified), the more difficult it becomes to answer the basic question of 'how big' the true influence of the BE is. We suspect that the contribution of the BE is, in most cases, relatively small compared to the contributions of socio-demographic and unmeasured variables (as implied by the elasticities reported and computed in the review article of Ewing and Cervero, 2001), but in any case it would be valuable for future studies to estimate it. For that contribution to be small would not render pointless any attempt to reshape the BE—as discussed elsewhere (e.g. Handy *et al.*, 2006), there are many reasons for improving the BE beyond influencing TB (such as increasing the diversity of available housing options), and even small contributions can be useful at the margin. But as long as changing TB *is* one of the reasons evinced for changing the BE, it is relevant to know how effectively that particular goal is likely to be met.

However, we must also point out that if the question is, 'Does the apparent influence of the BE diminish substantially once residential self-selection is taken into account?', the answer also tends to be a strong 'yes'. Given the extensive evidence that has accumulated on the impact of self-selection, we believe it is misleading to present empirical results that do not take that impact into account. Such faulty findings are likely to result in flawed policies, and/or an overestimation of their effectiveness.

Given the various limitations discussed throughout this paper, we are unable at this point to confidently specify the nature and extent of the causality between the BE and TB. In fact, those relationships differ by mode and trip purpose, as some studies have shown. They also differ depending on what elements of the BE are being captured. Specifically, many of the studies reviewed here focused on neighbourhood-specific characteristics such as density and land use mix, as opposed to aspects such as the regional location of the neighbourhood, though the latter could also be expected to influence TB—perhaps even more substantially, in some ways, than the former (Handy, 2006). Relationships are further likely to differ for different segments of the population, an issue not addressed by any of the empirical applications reviewed here (though most of the methodological approaches can accommodate it conceptually).

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Nevertheless, we can improve our understanding by designing studies to satisfy as many requisites of causality inference as possible. All the *statistical* methods used in the studies reviewed here can rely on the travel price changes suggested by Boarnet and Crane (2001) as a plausible causal mechanism, and all can be considered strong in terms of their ability to identify significant associations between the BE and TB. Thus, they differ only in how well they meet the non-spuriousness and time precedence criteria. In our view, approaches that explicitly include attitudes can perform well on the non-spuriousness criterion (by leaving little room for significant results to be due to spurious correlation with unmeasured variables), while those that permit multiple directions of causality and/or involve measurement at multiple points in time can excel on the time precedence criterion. In many cases of interest, the conceptual ideal is the longitudinal structural equations modelling approach, which can combine most of the strengths of the other methods: measurement of attitudes, allowance of multiple directions of causality and measurement at multiple points in time. If, when used to evaluate a 'treatment' such as a residential move or BE intervention, control groups as well as experimental groups are involved, this approach comes very close to being 'airtight' (though questions about generalizability could still remain, and the limitations discussed in the 'Empirical Studies by Methodology' section should be kept in mind). Although this method has not yet been fully operationalized in the present context (Cao *et al.*, 2007b, comes the closest, to our knowledge, but does not include a control group and is only quasi-longitudinal in that 'prior' measures are obtained only retrospectively and do not include attitudes—though *current* attitudes are measured), a project is underway in Australia (Giles-Corti *et al.*, 2008) which aims to do exactly that.

Thus, future studies adopting research designs that more closely resemble a true experimental design will lead to more definitive inferences regarding causality. Two types of studies are important (both of them ideally to include comparison groups of unaffected individuals similar in other relevant ways): (1) true panel studies of residents who move from one type of neighbourhood to another, with measurements of attitudes as well as socio-demographic traits and TB before and after, and further exploration of the reasons behind the move; and (2) natural experiments that examine the impact on TB in response to a change in the BE, such as the implementation of a traffic calming programme. Only by causal findings based on such evidence can we determine whether land use policies designed to increase opportunities for driving less and walking more will actually lead to the desired behavioural outcomes.

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Notes

1. A report (Cao *et al.*, 2008) contains additional detail related to both papers, which could not be incorporated into journal-length articles.
2. Of course, these biases are also possible with the design of the self-administered questionnaires from which the data for quantitative analyses are often collected. However, some scholars (e.g.

Dillman, 1978) suggest that all else being equal, the extent of at least the latter three biases could be more severe in the case of direct questioning, where the body language and tone of the interviewer can offer additional cues to the participants, and where (even in the case of a prepared script or set of questions) the interviewer generally has a certain amount of discretion over the spontaneous digressions that the interview might take.
3. They incorporated the IV approach into a technique known as a 'two-part model (2PM)', a variant on the Heckman sample selection model discussed in the next section.
4. Because this approach was not included in Mokhtarian and Cao (2008), we provide more detail on the methodology than we do for the other approaches.
5. The ± sign on w in the equation for RC^* indicates that a given unobserved factor could affect the sensitivity to a BE trait in one direction for RC and in the opposite direction for TB, depending on the definitions of each measure.
6. Mokhtarian and Cao (2008) only discuss this methodology in passing, since at the time of writing, they were not aware of an empirical application of the approach.

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