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Social Marketing and the Built Environment: What Matters for Travel Behaviour Change?

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Abstract

Social marketing and the built environment are two important ‘tools’ to manage travel demand. Most of the previous studies that evaluate the effects of social marketing programs have relied on pre- and post- surveys, using self-reported measures without any objective measures of travel behaviour change being included. In addition, many empirical studies that have looked at the connections between the built environment and travel behaviour have relied on cross sectional data, which limits the ability to make causal inference or identify policy implications. Furthermore, there is a lack of evidence on whether the effects of the built environment are synergistic when combined with other intervention programs, such as social marketing programs.

This paper is based on a unique panel data set from the TravelSmart program, one of the social marketing programs in Australia. Between 2005 to 2012, daily travel data were collected using GPS equipment in four Australian capital cities, Adelaide, Brisbane, Canberra, and Melbourne. All individuals in the targeted households aged over 14 carried a portable GPS device everywhere for a period of 15 days during September to November for each year from 2007 to 2012, providing a total of six waves of panel data.

This study aims to contribute by quantitatively evaluating the relative and combined effects of the TravelSmart and the built environment on travel behaviour using objective GPS measurements. The model results suggest that the TravelSmart program may have immediate effects on increasing walking but may not be as effective in reducing car trips and increasing bus trips. Also, the effects of the TravelSmart program do not appear to be sustained. In contrast, the built environment seems to have longer term effects on travel behaviour change, particularly on reducing the car trips.

1. Introduction

The challenge of climate change and the attention on public health have called for the changes on travel behaviour in many car-dependent countries. It is well recognized that car use is associated with series of negative social and personal effects, such as greenhouse gas emissions, air pollution, as well as obesity and other health problems related to sedentary lifestyles. By contrast, active travel and public transport are increasingly being promoted as alternatives to private car journeys because of their potential to provide gains in public health and improve the environment. These are some of the motivations for travel demand management measures which attempt to curb private car travel.

Social marketing programs have been implemented in many cities around the world as a travel demand management measures. These social marketing programs aim to change travel behaviour by providing individuals with information on using alternative transport to the car and helping them to realise the consequences of different travel modes on their health and the environment. Some programs also include public events, such as “ciclovias” or strategies such as used in the City of Portland’s ‘Sunday Parkways’, that close streets to cars for several hours for bicyclists and pedestrians as a way of highlighting the opportunities for not using a car. Social marketing programs are generally deemed a ‘soft’ measure of travel demand management since they focus on influencing individual psychological factors, such as attitudes and perceptions through information, campaigns and education. The outcome of social marketing programs on travel behaviour change appear promising although there are only a few studies which have quantitatively evaluated their effect and these have provided mixed results (Brög, 1998; Brög et al., 2009; Cooper, 2007; Dill and Mohr, 2010; Rose and Ampt, 2001; Rose and Marfurt, 2007). Also, most of the previous studies have relied on pre- and post- surveys using self-reported measures without any objective measures of travel behaviour change being included. Moreover, these studies have not typically focused on any long term effects which are addressed in this paper.

The built environment – its status and changes to it - has been another aspect of travel demand management with both transportation and public health disciplines realising the opportunity provided in using the built environment to change travel behaviour. In contrast to social marketing programs, changing the built environment is a ‘hard’ measure that affects travel behaviour by changing the generalised travel cost of the individual. Many empirical studies have looked at the connections between the built environment and travel behaviour and, although these studies have consistently found significant associations between the built environment and individual travel behaviour, the issue of investigating the causal relationship between travel behaviour and the built environment remains which limits the ability to make policy implications.

The contribution of this paper lies in a number of areas. First, the surveys are undertaken using GPS which provides more robust measures of travel behaviour than self-reported measures. Second, the paper uses repeated multi-wave data, providing true panel data that allows a comparison between households benefiting from social marketing advice and those who do not. Finally the study includes the role of the built environment in assessing the benefits or otherwise of the social marketing program as well as an input into policy development centred on the built environment, social marketing programs and travel behaviour.

The paper is organized as follows. The next section provides the literature context for the study and synthesises the literature with respect to social marketing and travel behaviour change on the one hand and the built environment and travel behaviour on the other. This is followed by a description of the data and the methodology used in the paper. The penultimate section provides results and discussion with the final section concluding the paper.

2. Literature Review

2.1 Effects of social marketing program on travel behaviour change

The early work on evaluating social marketing programs on travel behaviour change was conducted by Werner Brög and his company Socialdata. From the early 1990s, Brög (1998) undertook a series of experimental projects to prove the effectiveness of an individualised marketing program on public transport use. The experiment first classified the households into three groups - interested (I), regular users of public transport (R), and not interested (N). The experiment had motivation and persuasive periods, consultation phone calls and possible home visits which were conducted to solve the problems of requests of the Group I and Group R. Group I participants also received free tickets to use the public transport for a limited period of time. The experiments were successful, and a similar approach has now been applied in about 50 projects in 13 European countries. Through the individualised marketing program, the use of public transport increased quickly in nearly all projects without making any system improvements to the public transport itself (Brög, 1998).

Australia was among the earliest countries that applied the individualised marketing program in travel demand management outside Europe. Since about 2000, almost all states of Australia have introduced a voluntary behaviour change program known as *TravelSmart.* A review conducted by Taylor and Ampt (2003) concluded that consistent evidence was found in Australia to claim the TravelSmart program made substantial reductions in motor vehicle usage. Rose and Ampt (2001) evaluated two early trial projects conducted in Australia, one in Sydney and the other one in Adelaide. The qualitative analysis of the 50 participants in Sydney indicated that there was an increased awareness of the environmental consequences of using motor vehicles and significant intentions by participants to reduce their car travel. The quantitative analysis with 100 households in Adelaide indicated about a 10% reduction in vehicle kilometres travelled. However, the results of this latter study are limited by lack of a comparative control group.

The Ride to Work Day is an annual event that promotes bicycling to and from work in Victoria in Australia and fits as a special project within the TravelSmart category of programs. Rose and Marfurt (2007) quantitatively assessed the impact of this event on travel behaviour change using a pre- and post- survey. Their results showed about 27% of participants riding to work for the first time were still riding to work five months after the event with over 80% of the first time participants indicating that the event had a positive impact on their willingness to ride to work.

Social marketing programs have also been used in the United States as a means of travel demand management. Cooper (2007) evaluated the Washington State's King County Metro Transit's *In Motion* program, which was a community-based social marketing approach, and found a 24%-50% decrease in single occupancy driving and a 20%-50% increase in transit use. Dill and Mohr (2010) examined in three different neighbourhoods in Portland, Oregon the effects of City of Portland's *SmartTrips* program, which is similar to the *TravelSmart* concept of Australia. They found the effects of *SmartTrips* were not significant in one suburban neighbourhood, but were more positive in the other two neighbourhoods which had relatively better walkability.

Brög et al. (2009) reviewed the social marketing programs and their effects on travel behaviour change over three continents – Europe, Australia, and North America. In the UK, more than 600,000 people have been targeted in 24 *TravelSmart* projects since 2001, achieving a 12% reduction of car use. The *TravelSmart* project has also targeted 400,000 people in Perth, Australia where car trips were reduced by 11% in total. In North America, 18 *TravelSmart* projects were identified with reductions varying between 2% and 11% with an average reduction of 8%. As noted above, most evaluation studies have undertaken pre- and post- surveys with the post-surveys being conducted immediately following the project. In this review by Brög et al. (2009), only two studies monitored the long-term effects. Both studies concluded that the behaviour change achieved by the original intervention was sustained for several years. However, these long-term evaluations relied on self-reported measures (surveys) and lacked an objective and precise measure of behaviour change.

A recent review on soft transport policy measures by Richter et al. (2011) concluded that more panel studies are needed to investigate the long-term effects of social marketing programs so as to enable valid conclusions to be drawn and address the contradictory findings reported in previous studies. Other priorities for future research identified in this study included investigating how hard transport policy measures might increase the effectiveness of soft transport policy measures, whether social marketing programs have different impacts on different target groups, and research that could shed light on the determinants of travel behaviour change among different groups of participants.

This paper helps to address some of these issues through the use of data where the respondents carried a portable GPS device thus providing an objective measurement of travel behaviour as well as offering more evidence on the built environment effects found by Dill and Mohr (2010).

2.2 Effects of the built environment on travel behaviour change

The association between the built environment and travel behaviour is well established. A recent meta-analysis found that there are over 200 studies, most of which were completed since 2001 (Ewing and Cervero, 2010). The built environment affects travel behaviour by affecting the generalised cost of travel to various destinations (Boarnet and Sarmiento, 1998). The ''New urbanism' and related planning paradigms employing designs of higher density, mixed land use, and pedestrian-friendly design, can alter the time cost of travelling from one location to various other locations. It does this by concentrating trip origins closer to destinations and by influencing travel speeds. This is the theoretical underpinning for current empirical studies of built environment and travel patterns. Also based on this theory, travel demand models were constructed which integrated land use thus emphasising the connections between land use and travel behaviour. These models presume that travel demand is determined by three factors: generalised travel cost, income, and the social-demographic characteristics of traveller (Crane, 1996). The generalised cost is influenced by densities, street connectivity, and land use diversity, and thus land use is added as a vector in travel demand models with different degrees of complexity.

Although using different model specifications, most of empirical studies have concluded that a walkable neighbourhood featuring high density (Kitamura et al., 1997), mixed land uses (Frank and Engelke, 2005) and well-connected streets (Handy et al., 2002) is associated with more active travel and public transport use and less car use. However, this observed association between the built environment and travel behaviour does not inform the direction of causality. Several reasons have caused difficulties in establishing the causal link between the built environment and travel behaviour. The first is data limitations since a reasonable causal link model requires time precedence (direction of influence) which in turn requires panel data showing that changes in built environment characteristics at one point in time are associated with changes in travel behaviour at a later time (Cao et al., 2009), In practice this panel data is difficult to acquire. The second obstacle is the self-selection issue where residents who prefer to walk choose to live in more walkable neighbourhoods and those who prefer to drive choose to live in more drivable neighbourhoods, thus confounding the empirical evidence surrounding changes in the built environment and travel behaviour.

In recent years, research has tried to overcome these obstacles to explore the causal link from the built environment to travel behaviour. The first attempt in addressing the self-selection problem was by integrating subjective factors, such as attitude on travel and neighbourhoods preference, into the model (Cao et al., 2006; Handy, 2005; Handy et al., 2005). These studies concluded that neighbourhood characteristics retained a significant effect on travel behaviour after controlling the effect of self-selection, with the subjective factors playing an equally important or more prominent role than objective physical environment in explaining the variation of travel mode choice. A second approach was to employ modelling frameworks which overcome the drawbacks of the cross-sectional design, such as structural equation modelling (SEM).

Bagley and Mokhtarian (2002) first employed SEM in research on the connection between travel behaviour and the built environment finding the commonly observed association between land use configuration and travel patterns was not one of direct causality, but due primarily to correlations of each of those variables with others. In addition, their research also suggested that when attitudinal, lifestyle, and socio-demographic variables are accounted for, neighbourhood type has little influence on travel behaviour. However, a major limitation of this research was that it was not a strict causal link design since it used cross-sectional data to attempt to show these dynamic changes.

Cao et al. (2007) also employed SEM to investigate the relationship between changes in the built environment and changes in travel behaviour, but this time using a quasi-longitudinal design. Individual respondents were asked to recall their previous travel behaviour from one year before to indicate the changes of travel behaviour after they moved to new neighbourhoods. This study concluded that there was a causal connection from the built environment to driving and walking behaviour. Even though this study improved the data quality and methods, as compared to previous related studies, the study did not consider the changes of individual's attitude on travel behaviour over time nor the effect of these changes on travel behaviour, leading to the effects of built environment on travel behaviour being overestimated. A true panel design is needed to resolve this issue.

In addition to using SEM, Krizek (2003) explored causality by observing travel behaviour changes of households who had just relocated. This study found that households change travel behaviour when exposed to different urban forms. In particular, relocating to areas with high accessibility decreases the vehicle miles travelled. Although using longitudinal data, this study could not fully resolve the self-selection issue since differences in travel could be attributed to changes in preferences toward travel and/or residential location rather than simply to changes in built environment. Another way of exploring causality was undertaken by Cao (2010) using a propensity score methodology to estimate the causal influence of the built environment on travel behaviour, and here he found the built environment played a more important role in affecting walking behaviour than residential self-selection. The propensity score method helped to control for selection bias, which eliminated the effects of self-selection but again the cross-sectional nature of the sample meant this study still could not make a rigorous causal inference as to direction of influence since it lacked time precedence.

In summary, the literature demonstrates that a lack of longitudinal data has limited the ability to make rigorous causal inferences and thus evidence based policy suggestions. Furthermore, there is a lack of evidence on whether the effects of the built environment are synergistic when combined with other intervention programs, such as social marketing programs. This paper builds on previous studies to examine the relative and combined effects of social marketing and the built environment on travel behaviour change.

3. Data and Method

Since 2000, a number of localities in Australia introduced voluntary travel behaviour change initiatives, known as *TravelSmart*, as a social marketing program that provided information to participant households about their travel options with the goal of having households voluntarily reduce their car use, either by ride sharing, or by using public transport, bicycling, or walking in place of using a car.

Between 2005 to 2012, as part of evaluating this program, daily travel data were collected using GPS in four Australian cities, Adelaide, Brisbane, Canberra, and Melbourne, by the Institute of Transport and Logistics Studies (ITLS) of the University of Sydney (Stopher et al., 2009; Stopher et al., 2013). Individuals in the households aged over 14, carried a portable GPS device everywhere for a period of 15 days during September-November for each year from 2007 to 2012, providing a total of six waves of panel data. The panel covered about 120 households per year with about two thirds of the sampled households being *TravelSmart* participants. Of the 299 households that participated in various waves, 29 households (72 persons) have been included in five or more waves and this is the basis of the sample for this paper. All participants were required to fill in a paper form, which provided the socio-demographic details of the household and each member of the household, vehicle data and GPS usage information as well as carrying the GPS devices..

Table **1** shows the characteristics of the 29 households across each of the six waves. A decreasing trend of average number of vehicles could be seen for *TravelSmart* participants. The average number of bikes seems quite stable for *TravelSmart* participants, but has increased for Non-*TravelSmart* participants.

Table 1 Characteristics of Sampled Households

Year (Wave)	**Number of households**		**Average of number of vehicles**		**Average of number of bikes**	
	Travel Smart	Non- Travel Smart	Travel Smart	Non- Travel Smart	Travel Smart	Non- Travel Smart
2007 (Wave1)	14	6	2.07	1.33	2.09	0.40
2008 (Wave2)	19	10	2.05	2.00	2.06	0.88
2009 (Wave3)	19	10	1.95	1.60	2.25	1.33
2010 (Wave4)	19	10	1.89	1.70	2.12	1.10
2011 (Wave5)	19	10	1.84	1.60	2.29	0.89
2012 (Wave6)	16	9	1.69	1.78	2.20	1.71
All Waves			1.92	1.69	2.17	1.07

The GPS data have been processed by using software called G-TO-MAP, developed by the ITLS. G-TO-MAP has been shown to be reliable in detecting travel modes (Shen and Stopher, 2014). The five primary modes detected in this study include walk, bicycle, car, bus and rail. Due to the small percentage of bicycle and rail trips, this paper focuses on car, bus and walk trips. Following the mode detection, the time, distance and number of trips by each mode were calculated for each person and by each wave to provide the panel data. Combining all waves of GPS travel data for the 29 households generates 20582 individual trips from 3728 travel days and 1,103 non-travel days during the survey period.

The built environment was measured using Walk Score. Walk Score has been previously demonstrated as a valid and reliable measure of neighbourhood walkability (Duncan et al., 2011). Each participant was assigned a walkability score based on their home address. The resulting walkability score, ranging from 30 (car-dependent) to 83 (very walkable), suggested significant variations of the built environment among the households in the sample. The walkability score was then dichotomized, using median split. Then, by cross-tabulating *TravelSmart* and walkability scores, all participants were categorized into one of the following four quadrants: Non*TravelSmart*/LowWalkability; Non*TravelSmart*/HighWalkability; *TravelSmart*/LowWalkability; and *TravelSmart*/HighWalkability.

Scatterplots were first drawn to illustrate the differences in travel behaviour change between the groups. Considering the hierarchical structure of the data, with time points nested for each individual observation, multilevel modelling was employed to explore whether travel behaviour changed significantly over time. Compared to similar analyses conducted under a General Linear Model framework, multilevel models are seen as especially robust in the analysis of unbalanced data (Pinheiro and Bates, 2000) which is the case of the data used in this study. A difference-in-difference estimator was included in the model to test the effects of the social marketing program and the built environment on travel behaviour change. The multilevel model is specified as follows:

(Level 1) $$y_{ij} = \gamma_{0j} + \gamma_{1j}TIME_{ij} + \epsilon_{ij}$$

(Level 2) $$\gamma_{0j} = \beta_{00} + \beta_{01}Z_j + u_{0j}$$
$$\gamma_{1j} = \beta_{10} + \beta_{11}Z_j + u_{1j}$$

Where, y_{ij} represents the number of trips or trip time for person *i* at time point *j* (depending on model). Z_j represents the treatment effects, *TravelSmart* or walkability, at time point *j.* ϵ_{ij} is used for level-1 error term and u_{ij} is used for the level-2 error term.

Substituting the level-2 equation into the level-one equation, we get a single-equation form for estimation:

$$y_{ij} = \beta_{00} + \beta_{01}Z_j + u_{0j} + \beta_{10}TIME_{ij} + \beta_{11}Z_jTIME_{ij} + u_{1j}TIME_{ij} + \epsilon_{ij}$$

The model was estimated by Restricted Maximum Likelihood. The interaction term, Z_jTIME_{ij}, which is the difference-in-difference estimator, tests whether the treatment makes a difference in travel behaviour change.

4. Results and Discussion

To explore the different trends of travel behaviour over the four groups, scatterplots (with a locally weighted scatterplot smoothing) of the wave and number of trips were plotted separately for car (Figure 1), bus (Figure 2) and walk (Figure 3) to underpin the modelling. These descriptive results are discussed first before turning to the modelling results.

4.1 Descriptive results.

Figure 1 illustrates the changes of number of trips and trip time by car among the participants of the four groups. Comparing the two charts vertically provides an understanding of *TravelSmart* ,as affected by walkability. This shows the *TravelSmart* group and Non*TravelSmart* groups did show slightly different trends, particularly for the low-walkability group. In the high-walkability group, the differences were not significant, suggesting *TravelSmart* may have stronger effects on changing driving behaviour for those living in low walkable neighbourhoods. This might be expected since more driving is typically observed in low-walkability areas providing a greater opportunity for TravelSmart to produce change.

Comparing the charts horizontally allows effects of walkability on travel behaviour change to be observed, controlling for the *TravelSmart* effect. For the Non*TravelSmart* group, car trips made by participants living in high walkable neighbourhoods have decreased over time, while no significant changes for those living in low walkable neighbourhoods can be observed. This suggests that walkability may have an effect on reducing car trips over time, even without a social marketing intervention.

Figure 2 illustrates the changes of number of trips and trip time by walk mode for the participants of the four groups. In terms of the changes of total number of walk trips over time, participants of the four quadrants do not show significant differences. The differences are more evident in terms of total walking time. First, by vertical comparison, the *TravelSmart* group and Non*TravelSmart* group showed different trends, with total walking time consistently decreasing over time in Non*TravelSmart* group but slightly increasing from first to second wave and then decreasing in the *TravelSmar*t group. These differences suggest that *TravelSmart* might have short-term effects on encouraging walking but that this is not sustained into the longer term. Similar to the findings from car travel above, this difference was not found in the high-walkability group. Making the horizontal comparison, as above, suggests for the Non*TravelSmart* group, participants living in high-walkable neighbourhoods increased their walking time consistently over time. For those living in low-walkable neighbourhoods there is a different trend with decreases in walking time being observed over the same period: for the *TravelSmart* group, the walking time of the low-walkability group increased for the first wave and decreased thereafter, while no significant changes are observed for the high-walkability group. This suggests walking is a potential substitute for trips made by car for the high walkability group but not for those in the low walkability group. Car trips, because of the distances involved are more likely to be substituted by public transport trips for this latter group as discussed below.

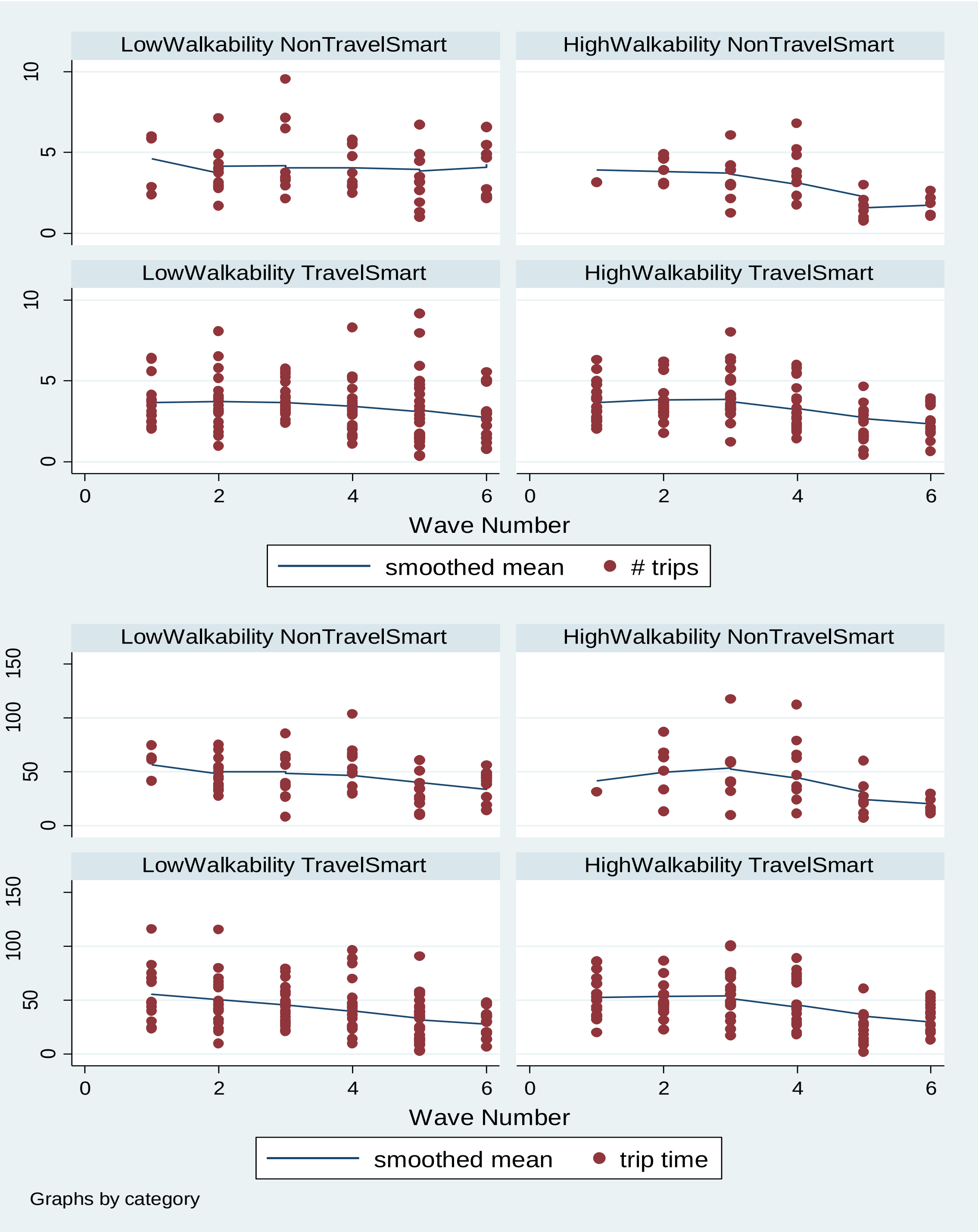

Figure 1 Changes of number of trips (top) and trip time (bottom) by car over time

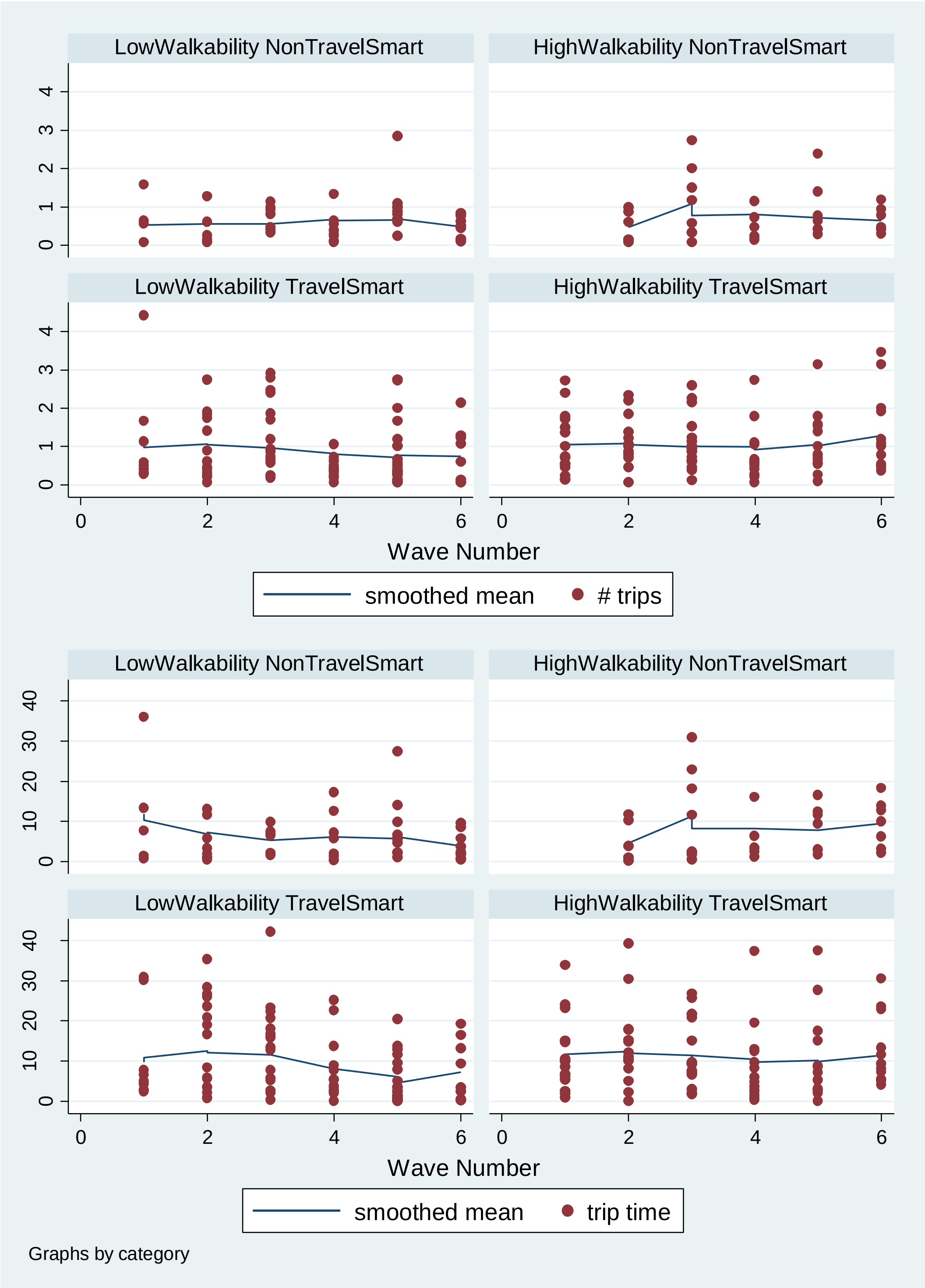

Figure 2 Changes of number of trips (top) and trip time (bottom) by walk over time

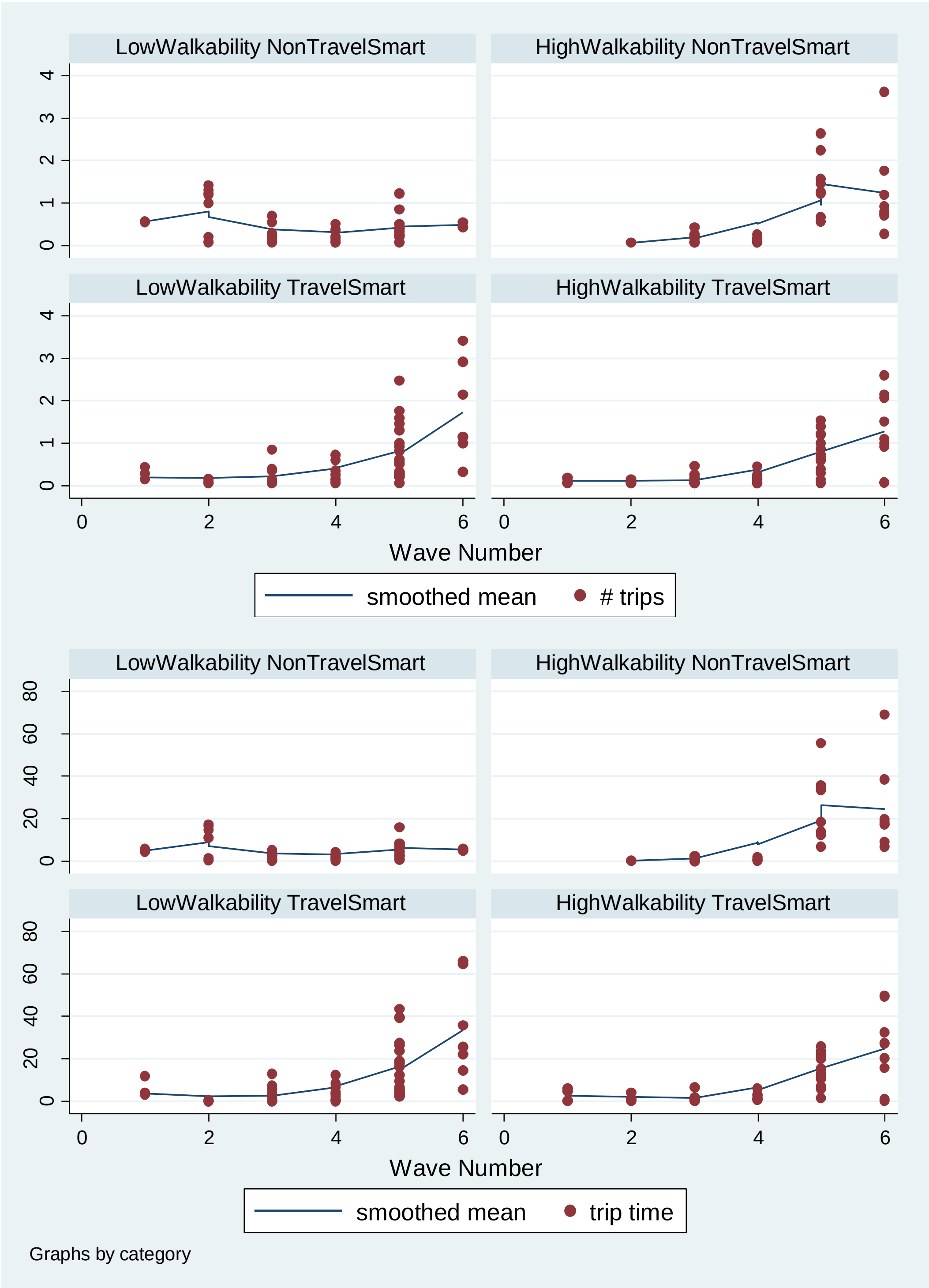

Figure 3 Changes of number of trips (top) and trip time (bottom) by bus over time

Figure 3 illustrates the changes of number of trips and trip time by bus among the participants of the four groups. As compared to the car and walk trips discussed above, bus trips showed much bigger changes over time. In terms of the number of trips, the *TravelSmart* group and Non*TravelSmart* group showed very different trends in the low-walkability environment, with the *TravelSmart* group continuously increasing their bus trips over the studied years while the Non*TravelSmart* group did not have significant changes. As discussed above, this is consistent with substituting public transport trips for car trips. Both *TravelSmart* and Non*TravelSmart* groups increased bus trips over years in the high-walkability environment. This suggests that some of the increase in bus trips might be attributed to *TravelSmart* for this group and some increase in bus trips to the nature of the built environment. The changes of total bus travel time of the four quadrants showed similar trends with the changes of number of bus trips.

In summary, *TravelSmart* appears to have a stronger effect on travel behaviour changes for people living in low-walkability environment than those in high-walkability environment. This is probably because people living in a high walkable neighbourhoods already have a relatively higher level of walking and higher number of bus trips as a result of the built environment and thus the potential of increase of these trips through other intervention programs was lower. Further, *TravelSmart* programs may also only have a short-term effect, while a walkable environment may have a long-term effect on promoting walking and bus travel, with or without other interventions.

4.2 Modelling the Effects of TravelSmart on travel behaviour change

The more descriptive approach of the previous section cannot take account of the socio-demographic background of the respondents and for this a modelling approach is required. As described in the methodology section above, multilevel models with a difference-in-difference estimator is employed to detect the effects of *TravelSmart* on travel behaviour change over time of the study, accounting for the socio-demographic characteristics of the respondents and their home environment (i.e. walkability). Separate models were conducted for each of the two dependent variables, number of trips and total trip time, and for each mode (e.g. car, walk, bus).

Table 2 Effects of *TravelSmart* on Travel Behaviour Change

	Car				Walk				Bus			
	# trips		Trip time		# trips		Trip time		# trips		Trip time	
	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Age	0.02	**0.03**	0.25	**0.05**	0.00	0.45	0.05	0.39	0.00	0.24	-0.05	0.52
Female	0.51	0.09	2.33	0.52	0.12	0.40	0.82	0.60	0.03	0.75	-0.64	0.73
numVehicles	-0.12	0.46	1.55	0.46	-0.01	0.93	-0.40	0.68	0.15	**0.04**	3.03	**0.03**
Householdsize	0.45	**0.00**	5.01	**0.00**	-0.02	0.81	-0.43	0.56	-0.08	0.10	-1.86	0.07
WalkScore	0.01	0.59	0.21	0.19	0.00	0.47	0.08	0.21	0.00	0.71	0.05	0.49
TravelSmart	-0.51	0.40	-1.19	0.88	0.51	0.13	0.77	0.84	-0.38	0.38	-1.03	0.90
wave 2	-0.27	0.63	-4.85	0.53	0.00	1.00	-6.28	0.11	0.04	0.91	0.49	0.95
wave 3	-0.05	0.92	-3.80	0.61	0.39	0.22	-2.43	0.52	-0.33	0.40	-3.93	0.61
wave 4	-0.03	0.95	0.04	1.00	-0.07	0.82	-5.70	0.14	-0.46	0.25	-5.59	0.46
wave 5	-1.43	**0.01**	-25.84	**0.00**	0.48	0.14	-2.78	0.47	0.29	0.47	8.52	0.26
wave 6	-0.96	0.08	-23.92	**0.00**	0.16	0.63	-3.72	0.34	0.46	0.27	13.32	0.10
TravelSmart x wave2	0.42	0.49	0.40	0.96	0.02	0.95	8.80	**0.04**	-0.14	0.78	-4.69	0.61
TravelSmart x wave3	0.48	0.43	2.27	0.79	-0.27	0.45	3.51	0.40	0.27	0.56	0.23	0.98
TravelSmart x wave4	0.10	0.87	-4.07	0.63	-0.37	0.30	1.63	0.71	0.43	0.34	2.62	0.76
TravelSmart x wave5	0.95	0.12	5.12	0.55	-0.62	0.08	-2.05	0.63	0.24	0.59	1.13	0.90
TravelSmart x wave6	0.43	0.50	6.31	0.47	-0.16	0.67	1.27	0.77	0.80	0.09	9.66	0.29
constant	1.05	0.42	8.86	0.59	0.41	0.53	4.91	0.51	0.69	0.20	5.69	0.59

Table 2 presents the model results, with statistically significant parameter results ($p<0.05$) being shown in bold font. The model results suggest that most of the variables are not statistically significant. This is not surprising given to the small sample size of this study. However, among the variables included in the model, the interaction terms - *TravelSmar*t x wave are the key variables of interest, as these indicate whether *TravelSmart* makes a difference in terms of travel behaviour change. Only one interaction term was found to be statistically significant and this is in the model with trip time of walking as the dependent variable. This suggests that the walking time of the *TravelSmart* participants increased significantly in wave 2, which was immediately after the intervention of the *TravelSmart* program. However, this effect did not last beyond the second wave suggesting only a short term impact. In addition, the model results indicated that older adults and bigger households had more car trips and longer driving times. Although the number of car trips and trip time by car both declined in wave 5 and wave 6, this is probably due to other reasons (e.g. increase of fuel price) which are not included in the modelling. A further potentially interesting result is that more household owned vehicles is associated with having more bus trips.

4.3 Modelling the Effects of walkability on travel behaviour change

Similarly, multilevel models with a difference-in-difference estimator is employed to detect the effects of walkability on travel behaviour change over time of the study, accounting for the socio-demographic characteristics of the respondents and the effects of *TravelSmart*. Separate models were conducted for each of the two dependent variables: number of trips and total trip time, and for each mode (e.g. car, walk, bus).

Table 3 Effects of Walkability on Travel Behaviour Change

	Car				Walk				Bus			
	# trips		Trip time		# trips		Trip time		# trips		Trip time	
	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Age	0.02	0.10	0.18	**0.14**	0.00	0.40	0.05	0.35	0.00	0.24	-0.05	0.52
Female	0.51	**0.08**	2.34	0.52	0.12	0.38	0.83	0.60	0.06	0.51	-0.28	0.88
numVehicles	-0.03	0.84	1.68	0.42	-0.04	0.66	-0.86	0.38	0.16	**0.02**	3.22	**0.02**
Householdsize	0.34	**0.00**	4.43	**0.01**	0.01	0.90	0.08	0.92	-0.09	**0.09**	-1.83	**0.08**
TravelSmart	-0.11	0.73	-0.49	0.90	0.21	0.16	2.75	0.10	-0.06	0.53	0.60	0.75
Walkability	0.05	0.91	-1.08	0.86	0.14	0.59	0.97	0.74	-0.16	0.66	-1.84	0.79
wave 2	0.03	0.93	-6.40	0.15	-0.02	0.94	0.47	0.85	0.03	0.91	-2.44	0.64
wave 3	0.38	0.23	-6.59	0.14	0.20	0.32	-0.29	0.90	-0.12	0.63	-3.32	0.51
wave 4	0.13	0.69	-4.49	0.32	-0.41	**0.04**	-4.07	0.10	-0.11	0.67	-2.98	0.56
wave 5	-0.27	0.39	-20.05	**0.00**	0.00	1.00	-4.94	**0.03**	0.29	0.26	6.29	0.20
wave 6	-0.14	0.68	-19.58	**0.00**	-0.15	0.50	-4.13	0.12	1.18	**0.00**	22.07	**0.00**
Walkability x wave2	0.18	0.71	4.71	0.48	-0.02	0.95	-0.26	0.94	-0.11	0.82	1.16	0.89
Walkability x wave3	-0.05	0.92	10.36	0.11	-0.07	0.80	1.36	0.68	0.03	0.95	-0.07	0.99
Walkability x wave4	-0.05	0.92	4.51	0.49	0.11	0.71	0.28	0.94	-0.04	0.93	-0.89	0.91
Walkability x wave5	-1.10	**0.02**	-5.73	0.40	0.04	0.88	3.11	0.36	0.46	0.23	7.55	0.31
Walkability x wave6	-0.99	**0.05**	-0.10	0.99	0.28	0.36	3.86	0.29	-0.20	0.64	-2.55	0.76
constant	1.54	0.07	25.73	0.02	0.86	0.06	6.84	0.19	0.56	0.17	7.52	0.35

Table 3 presents the model results, with statistically significant parameter results ($p<0.05$) being shown in bold font. Among all the interaction terms, only two of them, Walkability x wave5 and Walkability x wave6, were statistically significant, suggesting that those living in high-walkability neighbourhoods decreased their driving more than those living in low-walkability neighbourhoods in wave 5 and wave 6. This indicates that the built environment may help to reduce car trips. In addition, the model results suggest that older adults and bigger households tended to have longer car trips, while bigger households had less bus trips.

4.3 The combined effects of Travel Smart and walkability on travel behaviour change

To explore whether the effects of *TravelSmart* on travel behaviour change were different between walkable and non-walkable neighbourhoods, the multilevel models with the interaction, *TravelSmart x walkability x wave*, was also undertaken for each dependent variable. However, most of the interactions were not statistically significant which is attributed to the small sample size. Although the descriptive analysis suggests that *TravelSmart* might have a stronger effect on travel behaviour change for participants living in low-walkability neighbourhoods, the model results have not confirmed this finding. Future research with a larger sample size are needed to test this hypothesis.

5. Conclusions

Social marketing and the built environment are two important tools to manage travel demand. This study contributes by evaluating the relative and combined effects of these two measures on travel behaviour, relying on six-wave panel data collected from 72 persons in 29 households in Australia.

The descriptive analysis of this study finds that the *TravelSmart* program has stronger effects on travel behaviour change for the participants living in low-walkable neighbourhoods than for those living in high-walkable neighbourhoods. This is probably because of residential self-selection effects. Participants living in high-walkable neighbourhoods might already hold positive attitudes and perceptions towards active travel and public transport, and thus have higher levels of walking and bus trips. The attempt to further change their attitudes and perceptions through the *TravelSmart* program may therefore have a lower impact as compared to those living in low-walkable neighbourhoods, where many participants may hold negative attitudes and perceptions toward walking and public transport, and have high level of car use before the intervention. However, given the very small sample size of this study, this finding is not confirmed by the model results.

Given to the findings of this study, social-marketing interventions that aim to promote sustainable transportation look as though they need to be implemented on a more continuous basis. This study supports the development of targeted interventions which are specific to the built environment of the neighbourhood including neighbourhood specific based marketing materials that include information on the location of safe walking and bicycle routes and walking and bicycle safety facts and tips. Such materials should be permanently available and free to order from the government website to encourage permanent marketing of travel behaviour change as has been done with the IndiMark trials in Australia and elsewhere (Richter et al., 2011). Other public events, which are associated with higher cost, could be implemented on a monthly or yearly basis.

Further, walkable neighbourhood environments, featured with relatively high density, connected streets, mixed land-use and good accessibility, may have longer-term effects on reducing car trips and be synergetic with social marketing activities. Urban sprawl is pervasive in Australia (Newman and Kenworthy, 2000), and as a consequence, many Australian cities have become dependent on the car travel. The adverse impact of car-dependent travel patterns on social equity, environment and public health has been well documented and this should be an extra spur to the development of policies that encourage dense and walkable environments in Australian cities to achieve the goal of equity, low-carbon, health, and sustainability.

This paper has limitations. First, the relatively small sample size limits the robustness of statistical models. A larger panel is needed to confirm and generalise the findings from this study. Second, the Walk Score measure has not been validated in the Australian context, though it has been found to be positively associated with the duration of walking for transport in Australia (Cole et al., 2015). Third, the study did not explore the mechanism of travel behaviour change resulted from social marketing change or the built environment impact.

Future research employing psychological theories, such as theory of planned behaviour (Ajzen, 1991), to investigate the change of psychological factors (including attitudes, social norms, perceived behaviour control, and intentions) after the interventions of social marketing program or built environment could be another avenue to understand the mechanism of behaviour change. Although data dependent, a comparison of the effects of social marketing programs implemented in different regions would also be enlightening. Finally, our sample is based on the single respondents that make up a household. It is possible, and is an avenue for further research, to examine how different the results are at a household level. This would explore the hypothesis as to whether there is compensatory behaviour being undertaken within a household with the reduction of car trips perhaps leading to more trip chaining or activities being undertaken by different members of the household. Identifying whether household behaviour change may be different from the travel behaviour change of the individual is an important next step as part of a wider exploration of the possible synergistic effects of social marketing programs and the built environment.

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