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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 which have had significant attention in the literature separately. Most previous studies evaluating 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. Further, 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 study contributes by quantitatively evaluating the relative and combined effects of the *TravelSmart* and the built environment on travel behaviour using objective GPS measurements. Between 2012 and 2014, daily travel data were collected using GPS equipment in suburbs of inner northern Adelaide, South Australia. Individuals in the households aged over 14 carried a portable GPS device everywhere for a period of 15 days during March–May in each year from 2012 to 2014, providing a total of three waves of panel data. The empirical analysis suggests that the *TravelSmart* program as a 'treatment' significantly reduced the car trips soon after implementation with longer term effects on reducing car trips in high-walkable neighbourhoods. For walking and bus trips, the *TravelSmart* program increased these 1 year after the 'treatment' with stronger effects on travel behaviour change for the participants living in high-walkable neighbourhoods than for those living in low-walkable neighbourhoods.

Keywords Social marketing · GPS survey · *TravelSmart* program · Built environment · Walkability

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Introduction

The challenge of climate change and the attention on public health have called for changes in travel behaviour in many car-dependent countries. It is well recognized that car use is associated with a series of negative social and personal effects, such as greenhouse gas emissions, air pollution, obesity and other health problems related to sedentary lifestyles. In 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, to highlight 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 the long term effects which are a focus of this paper.

The built environment—its status and changes to it—has been another 'tool' 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. 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 and this limits the ability to make policy implications.

The contribution of this paper lies in a number of areas. First, the surveys are undertaken using Global Positioning System (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 allow a comparison between households benefiting from social marketing advice and those who do not (providing 'treatment' and 'control' samples). 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.

Literature review

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). However, the conclusion of this study was based on a simple comparison of the changes of public transport use between treatment and control groups, before and after the marketing program. It is not clear that the differences between the two groups were statistically significant or not.

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 good 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 follow up survey which is 5 months after the event. Their results showed about 27 % of participants riding to work for the first time were still riding to work 5 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. However, the follow up survey only targets the individuals who registered for the event. This might overestimate the effects of the Ride to Work Day event because individuals who registered and participated in this event are more like to be those who are interested on cycling to work, and they may ride to work even without participating the event. Including a control group that consists of people who are also interested in cycling to work but who had not participated in this event would provide more rigorous evidence.

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, a community-based social marketing approach, and found a 24–50 % decrease in single occupancy driving and a 20–50 % increase in transit use. Although the results show promising results of the *In Motion* program, we do not whether these changes in travel mode share sustained in a longer term. Dill and Mohr (2010) examined in three different neighbourhoods in Portland, Oregon the effects of City of Portland's *SmartTrips* program, a program similar to the *TravelSmart* concept in Australia. They found the effects of *SmartTrips* sustained beyond 1 year and up to a least 2 years, and the effects were not significant in one suburban neighbourhood, but were more positive in the other two neighbourhoods which had relatively better walkability. The data analysis of this study is based on simple comparisons of the means between the treatment and control group, and this limits the ability to make strong causal inferences.

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).

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 have been constructed with 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 other 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 panel data are 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 strictly identifying causal link 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 1 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 have 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.

Synergistic effects of social marketing and the built environment on travel behaviour change

The review above points to a lack of studies discussing and investigating the synergistic effects of the built environment (hard measures) and the social marketing (soft measures) on travel behaviour. This section presents a conceptual model (Fig. 1) to illustrate how the effects of social marketing might vary with different types of neighbourhood built environments and how the social marketing program might moderate the effects of the built environment on travel behaviour.

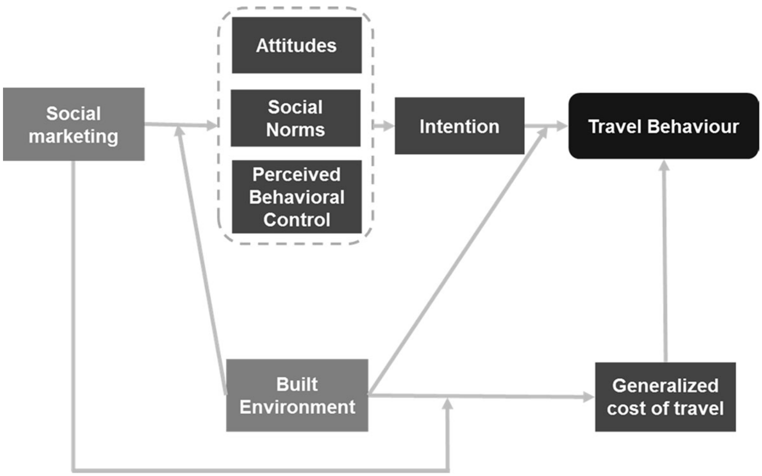

Fig. 1 A conceptual framework

The theory of planned behaviour (TPB; Ajzen 1991), a widely used theory in social psychology, has been employed as a theoretical framework to explain the mechanism of intervention effects of social marketing programs on changing travel behaviour (Bamberg et al. 2011; Dill and Mohr 2010). Based on this theory, the social marketing influences people's travel decisions by altering their attitudes towards different travel modes, by influencing their opinions on the travel choices of their family members, friends and others who are important to them, and by empowering them to choose alternative travel options. The built environment, however, could moderate the effects of social marketing on these psychological factors. For example, it is easier to advocate pro-walk or pro-bike attitudes using social marketing programs in a walkable neighbourhood than in a car-dependent neighbourhood. In addition, if a household lives in a walkable neighbourhood, they are more likely to provide support for family members or friends to walk or bike, because there may be less worries about for example, about safety of walking and biking in the neighbourhood. Further, a walkable neighbourhood provides pedestrian and bicycling friendly amenities and facilities that help people to feel confident and capable of switching from car trips to active modes. In other words, without a supportive built environment, the travel attitudes, social norms and perceptions are very much more difficult simply through a social marketing program. Finally, the built environment could moderate the link from these psychological factors to travel behaviour. Even if an individual's attitudes and perceptions are changed after the intervention of a social marketing program, and they state an intention to change their travel behaviour, actual behaviour change is likely to depend on the built environment. For example, it is difficult for people living in a car dependent neighbourhood to choose walking and bicycling as travel modes because of environmental constraints, such as no accessible business establishments, no pavements or bike paths or high traffic volume even they have the intention to use walk and bike more for utilitarian purposes.

On the other hand, it may be that the social marketing program may moderate the relationship between the built environment and travel behaviour. As discussed above, the built environment influences travel behaviour by changing the generalized travel cost, including both actual and perceived travel cost. A social marketing program could intervene by affecting the perceived travel cost. For example, through advocating and educating, the social marketing program may make individuals realise the health and environmental benefits of active travel, thereby creating a more positive attitude and perception of active travel, which in turn may further shorten the psychological distance of travel, over and above any change due to changes in actual distance travelled through an implementation of, for example, a built environment change that changes land use mix.

The above discussion shows that the built environment and the social marketing program are interdependent. On the one hand, the effect of a social marketing program on travel behaviour change is more limited without a built environment to support alternative travel. On the other hand, the social marketing program could strengthen or help to reap the full benefits of the built environment in promoting sustainable travel.

Data and methods

Data collection

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. Two approaches were used in the *TravelSmart* program: a community development approach and an individual conversation based approach (Government of South Australia 2009). The two approaches were delivered simultaneously over the life of the *TravelSmart* project. The community engagement approach was undertaken by identifying people and groups who were passionate about the *TravelSmart* message in their community. This included people with potentially high influence with good community networks, groups with large membership and people with particular needs (e.g. people about to lose their licence). Community groups were engaged through either attending a public event or meeting, or responding to a *TravelSmart* article in a newsletter. Some individual members of groups had personal conversations with a *TravelSmart* officer to discuss their transport issues and were subsequently engaged as a participating household. For individual engagement, *TravelSmart* officers had a guided conversation with at least one person in the household either over the phone or in person. The intention was for the TravelSmart officer to identify the motivations and frustrations about their travel behaviour through talking through the negative aspects of car use, and to use this to provide information specific to the individual. Along with a guided conversation, tools were provided to each household to address their specific needs and to assist them to reduce their car use. These tools included, but were not limited to, a brochure providing step by step instructions to plan journey by public transport and bike, a map for people who wanted to walk/cycle more or take a specific route, a letter to praise past reduction in car km and to reinforce the benefits, a letter to remind participant of the changes they committed to during the conversation, guides to local shops, services, clubs and activities to assist people to use local alternatives. The details of *TravelSmart* approach and the full suite of instruments can be found at Government of South Australia (2009).

Between 2012 and 2014, as part of evaluating this program, daily travel data were collected using GPS in suburbs of inner northern Adelaide, by the Institute of Transport and Logistics Studies (ITLS) of the University of Sydney (Stopher et al. 2009, 2013). Individuals in the households aged over 14, carried a portable GPS device everywhere for a period of 15 days during March–May for each year from 2012 to 2014, providing a total of three waves of panel data. 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.

Households were recruited from lists provided by the South Australia Department of Planning, Transport, and Infrastructure (SA DPTI), derived from driver licence renewal lists. Because these lists only included people with listed telephone numbers, investigation was undertaken to determine what proportion of households in Adelaide may have unlisted telephone numbers. From this, it was determined that the proportion was sufficiently high that it would be desirable to obtain part of the sample through random digit dialling, which should capture some of those households with otherwise silent numbers.

The first wave of data collection commenced in March 2012, with personnel from ITLS at the University of Sydney using a computer assisted telephone interviewing (CATI) script to recruit households in the target area from a random sampling of the driver license listings, and also randomly generated telephone numbers. The randomly generated telephone numbers were obtained by adding or subtracting one from existing listed phone numbers and checking these numbers against the full list of driver license renewals, to make sure that there were no duplicate listings. Recruitment was completed by mid-June. Following recruitment, lists of recruited households were provided to personnel at SA

DPTI for delivery of GPS devices. SA DPTI personnel delivered devices personally, along with the required forms, and later retrieved the devices and completed forms. Data on the devices were downloaded and the devices could then be re-used, if the timing permitted. The first wave of data were collected just before the implementation of *TravelSmart* program and is the before ‘treatment’ observation. The final eligible sample comprised 332 households that were successfully recruited, less 19 households that subsequently dropped out, leaving a final total of 313 households.

The *TravelSmart* program was rolled out in inner northern Adelaide, beginning in mid-2012 and continuing to the later part of 2013. A second wave of GPS survey commenced between April, 2013 and May, 2013, immediately after the implementation of *TravelSmart*. Of the 313 households recruited in Wave 1, 213 households were recruited in Wave 2. Overall attrition amounted to 32 percent, consisting of 19 households that dropped out prior to Wave 2, 49 households that refused to participate in Wave 2, and 32 households that were ineligible. From the 213 households that were recruited, a further 6 households did not participate after having agreed to undertake Wave 2. This left 207 households. From these 207 households, 166 provided data for all persons in the household eligible to carry a GPS device, 35 provided data for at least one eligible person, and 6 provided no data. Thus, the final sample from Wave 2 consisted of 201 households with full or partial data.

In order to explore the longer term effects of *TravelSmart*, a third wave of data collection was conducted in April, 2014, approximately 1 year after the implementation of *TravelSmart*. Those households that had responded in either or both of Waves 1 and 2 were contacted and asked if they would be willing to participate in a third wave of the study. The initial list of households for recruitment comprised 246 households, including the 213 recruited in wave 2 and an additional 33 households that had responded to Wave 1, but had been unavailable or uncontactable in Wave 2. Of the 246 households, 144 households were recruited and provided valid data in Wave 3. Table 1 provides a summary of the recruitment process.

Data processing

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 [including car trips as a driver or as a passenger (and not being able to distinguish between these is a common limitation of GPS based data collection)], bus and rail. Due to the very small percentage of rail and bike 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.

Table 1 Summary of recruitment process

	First wave	Second wave	Third wave
Recruitment time	March–June 2012	April–May 2013	April–May 2014
Number of households recruited	332	213	149
Number of recruited households with valid data	313	201	144

The built environment around each participant's home was measured using Walk Score. Walk Score has been previously demonstrated as a valid and reliable measure of neighbourhood walkability (Carr et al. 2010; Duncan et al. 2011; Manaugh and El-Geneidy 2011) and has been used in Australian context (Cole et al. 2015). Each participant was assigned a walkability score based on their home address. The resulting walkability score, ranging from 9 (car-dependent) to 88 (very walkable), suggested significant variations of the built environment among the households in the sample. The walkability score was then dichotomized, using median split, into two groups: high walkability and low walkability.

Sample characteristics

This study focused on the travel behaviour change corresponding to the *TravelSmart* at the *individual* level. Only those with valid 15 days' GPS data were included in the analysis. Table 2 shows the basic characteristics of the 341 individuals who were recruited and provided valid data at Wave 1. Among the 341 individuals, 245 participated in *TravelSmart* after the recruitment and are the 'treatment' group. The 96 participants not participating in *Travel Smart* are the 'control' group. There were no statistically significant differences between the two groups before 'treatment' at Wave 1.

The sample characteristics between the three waves were also compared and results are presented in Table 3. As shown by the *p* values, no significant differences were detected in terms of socio-demographics between the samples from the three waves, indicating that sample attrition over time is not systematic, and should not cause serious attrition bias.

The travel behaviour was measured using three dependent variables: number of trips per day, total trip time per day (min), and total trip distance per day (km). The descriptive analysis of each dependent variable at each wave is provided in Table 4.

Modelling methods

The first objective of this paper is to evaluate the effects of *TravelSmart* on travel behaviour change. Difference-in-differences (DD) models were employed to explore whether there were significant differences between treatment group (*TravelSmart* participants) and control group (Non-*TravelSmart* participants) in terms of travel behaviour changes (first difference), before and after the implementation of *TravelSmart* (second difference). DD models for estimating the effect of policy implementation have become very popular in economics and other social sciences (Athey and Imbens 2002). DD estimation compares the difference in outcomes before and after the intervention for groups affected by it to this

Table 2 Characteristics of treatment and control group at Wave 1

	Non-*TravelSmart* (n = 96)	*TravelSmart* (n = 245)	*p* values
Age	48.96	50.57	0.47
% Female	53 %	55 %	0.78
Household size	2.88	2.82	0.77
#Vehicles	2.01	2.10	0.46
#Bikes	1.93	1.71	0.38
Walk score	55.06	53.79	0.53

Table 3 Characteristics of sampled participants from Wave 1 to Wave 3

	Wave 1 (n = 341)	Wave 2 (n = 309)	Wave 3 (n = 179)	*p* values
Age	50.11	51.07	49.63	0.66
% Female	1.54 %	1.55 %	1.58 %	0.72
Household size	2.84	2.77	2.84	0.81
#Vehicles	2.07	2.03	2.08	0.78
#Bikes	1.77	1.65	1.73	0.71
Walk score	54.15	53.97	53.33	0.87

Table 4 Descriptive analysis of the dependent variables

	Wave 1		Wave 2		Wave 3	
	Mean	SD	Mean	SD	Mean	SD
Number of car trips	2.733	1.355	2.434***	1.308	2.436**	1.357
Number of bus trips	0.696	0.516	0.462***	0.453	0.633	0.464
Number of walk trips	0.794	0.686	0.635***	0.694	0.778	0.790
Car trip time (min)	31.359	20.461	27.775***	17.673	25.876***	17.342
Bus trip time (min)	14.576	14.580	13.642	10.482	13.156	10.645
Walk trip time (min)	7.701	9.960	7.749	11.475	7.062	9.334
Car trip distance (km)	19.084	14.866	17.745	13.332	16.939*	14.089
Bus trip distance (km)	7.332	6.649	7.093	5.728	7.073	5.929
Walk trip distance (km)	0.707	0.942	0.672	1.106	0.641	0.818

*, ** and *** denote the value is different from the value of Wave 1 at the 10, 5, and 1 % level, respectively, based on repeated measure ANOVA tests

difference for unaffected groups (Bertrand et al. 2002). DD models can rule out all time-invariant unit-level factors which may not be observable or measureable but may lead to omitted variable bias (Card and Krueger 1993). DD estimation is also attractive because its simplicity as well as its potential to avoid many of the endogeneity problems that typically arise in OLS regression (Bertrand et al. 2002). Separate models were developed for each of the three travel modes: Car, Bus, and Walk. The DD model is specified as:

$$y_{it} = \beta_0 + \beta_1 TS_{it} * Wave2 + \beta_2 TS_{it} * Wave3 + \beta_3 TS + \beta_4 Wave2 + \beta_5 Wave3 + \delta_i + \epsilon_{it} \quad (1)$$

where y_{it} represents the three dependent variables for person i at time point t. β_0 is the constant, which is the mean of y_i at Wave 1. TS_{it} is an indicator variable that takes value equal to 1 if individual i participated in *TravelSmart*, and 0 otherwise. The individual fixed effects δ_i included in the model controls non-parametrically for unobservable individual-invariant characteristics. ϵ_{it} is the error term. β_1 and β_2 are the coefficients of DD estimators, which test whether *TravelSmart* participation has made a difference to travel behaviour change immediately after the implementation of *TravelSmart* and 1 year after implementation. β_3 is the main effect of *TravelSmart*, and β_4 and β_5 are the main effects of Wave 2 and Wave 3. Figure 2 illustrates the difference-in-differences models.

The second objective of this paper is to investigate whether the effects of *TravelSmart* varies among neighbourhoods with different levels of walkability. Walkability was defined as an indicator variable that takes a value equal to 1 if the individual *i*'s home environment with a Walk Score above 56 (the median of Walk Score for all *i*), and 0 otherwise. A difference-in-difference-in-differences (DDD) model was specified as an extension of the DD model:

$$\begin{aligned} y_{it} = \beta_0 &+ \beta_1 TS_{it} * Wave2 + \beta_2 TS_{it} * Wave3 + \beta_3 Wave2 * walkability_{it} \\ &+ \beta_4 Wave3 * walkability_{it} + \beta_5 TS_{it} * Wave2 * walkability_{it} \\ &+ \beta_6 TS_{it} * Wave3 * walkability_{it} + \beta_7 TS + \beta_8 Wave2 + \beta_9 Wave3 + \delta_i + \epsilon_{it} \end{aligned} \tag{2}$$

Here, β_5 and β_6 are the coefficients of DDD estimators, which test whether the *TravelSmart* has different effects on travel behaviour change in low and high walkable neighbourhoods. To account for the nested structure of the data (i.e. individuals within households), clustered standard errors were used in all models (Cameron and Miller 2015).

Results and discussion

Does *TravelSmart* affect travel behaviour?

To evaluate the effects of *TravelSmart* on travel behaviour change, separate DD models were estimated using the model specification presented in Eq. (1) for each of the three dependent variables and for each of the three travel modes. In total, nine models were estimated, and individual fixed effects were included in all models to account for the unobserved individual effects. The model results are presented in Table 5. As we used an individual fixed effects model, the treatment variable is necessarily collinear with the fixed effects (if an individual belongs to *TravelSmart* in time = 1, they will also belong at time = 2 and time = 3), and this leads to the *TravelSmart* variable being omitted from the

Fig. 2 Difference-in-differences model

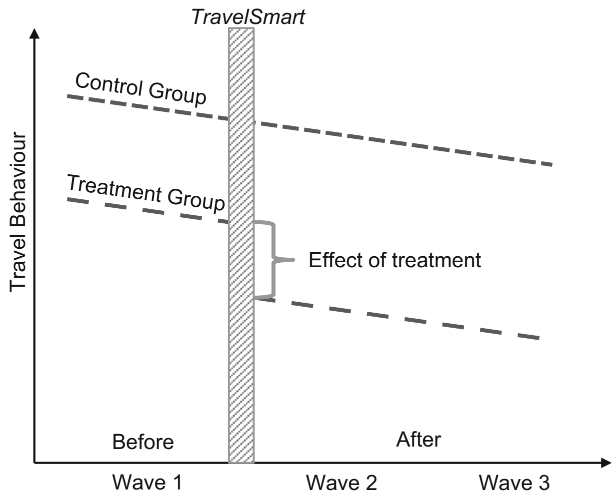

Table 5 Effects of *TravelSmart* on travel behaviour change

	Coefficients estimated (absolute value of robust t statistics)								
	Number of trips			Total trip time (min)			Total trip distance (km)		
	Car	Bus	Walk	Car	Bus	Walk	Car	Bus	Walk
Wave 2	−0.08 (0.41)	−0.31 (4.09)***	−0.29 (2.93)***	2.69 (1.02)	−2.75 (1.34)	0.06 (0.05)	2.54 (1.11)	−0.91 (0.90)	−0.09 (0.78)
Wave 3	−0.21 (1.06)	−0.17 (2.30)**	−0.17 (1.79)*	−3.07 (1.16)	−4.23 (2.06)**	−2.97 (2.45)**	−0.38 (0.16)	−1.39 (1.36)	−0.35 (2.91)***
Wave 2 × TS	−0.30 (1.27)	0.10 (1.16)	0.17 (1.52)	−8.58 (2.77)***	2.48 (1.04)	−0.01 (0.01)	−5.30 (1.98)**	0.92 (0.77)	0.08 (0.58)
Wave 3 × TS	−0.12 (0.50)	0.15 (1.70)*	0.22 (1.90)*	−3.30 (1.06)	3.84 (1.60)	3.18 (2.25)**	−2.42 (0.90)	1.55 (1.30)	0.39 (2.76)***
Constant	2.73 (37.37)***	0.70 (25.14)***	0.79 (22.29)***	31.36 (32.32)***	14.58 (19.42)***	7.70 (17.36)***	19.08 (22.76)***	7.33 (19.63)***	0.71 (15.93)***
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.65	0.62	0.72	0.68	0.54	0.78	0.58	0.56	0.75
Observations	537	537	537	537	537	537	537	537	537

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

final model results. Typically soft measures such as *TravelSmart* depend on targeting appropriate segments and so controlling for the socio-demographic of the treatment set is important to answer our research questions as to whether the *TravelSmart* changed behaviour and whether there is a difference between residents living in different built environments. The use of a fixed effect model offers robust results by accounting for both observed and unobserved individual characteristics as compared to models which include only a limited set of demographic variables and do not control for any unobserved effects. This estimation approach is equivalent to an estimation without individual fixed effects but with a dummy variable for each individual: this estimation was also performed showing many of the individual dummies being statistically significant and contributing, therefore, the power of the explanation of the model.

The first three columns of Table 5 present the model results that estimate the effects of *TravelSmart* on total number of trips by each travel mode. The key variables of interest are the DD estimators, β_1 and β_2, which are the interaction between Wave and *TravelSmart*. The model results indicate that most of DD estimators are not statistically significant. Most previous studies have been unable to test the significance of the 'treatment' of *Travel Smart* because they did not include a control group in their study design. The results shown in Table 5 for the impact of the *TravelSmart* effect is very consistent with the average effects (of around 10 %) of other social marketing programs reported by previous studies (Brög et al. 2009; Taylor and Ampt 2003), although it is statistically not significant. For example, the number of car trips decreased by 11 % (0.30/2.73) in Wave 2, after the implementation of *TravelSmart*. Table 5 shows the effects of *TravelSmart* on increasing bus and walk trips were significant at ten percent level in the Wave 3, which is about 1 year after the implementation of the *TravelSmart*. This suggests that increasing alternative travel to cars takes time after the *TravelSmart* implementation. In particular, the number of bus trips and walk trips increased by 0.15 and 0.22 trips per day from Wave 1 to Wave 3, representing an increase of 22 (0.15/0.70) and 27 % (0.22/0.79) in bus trips and walk trips respectively.

The three columns in the middle of Table 5 present the model results that estimate the effects of *TravelSmart* on total trip time by each travel mode. This shows *TravelSmart* had a very significant and strong effect on reducing the trip time by car. On average, *TravelSmart* participants reduced their time spent on car travel by about 5.89 (2.69–8.58) min per day from Wave 1 to Wave 2, which is approximately a reduction of 18 % (5.89/32.94) from Wave 1. In contrast, the non-*TravelSmart* participants increased their time spent travelling by car from Wave 1 to Wave 2 but this difference is not statistically significant. The effects of *TravelSmart*, therefore, are the difference in car trip time change between the *TravelSmart* and non-*TravelSmart* participants, which is an 8.58 min (or 27 % = 8.58/31.36) reduction of car trip time. However, the effects of *TravelSmart* on reducing the car trip time were not significant by Wave 3. This suggests the effects of *TravelSmart* on reducing car trip time were not sustained. The effects *TravelSmart* on walking time were not significant in Wave 2, but became significant in Wave 3. Again, as with the discussion on number of trips above, this suggests that the effects of *TravelSmart* on promoting alternative travels to car may take a longer time to come to fruition. In particular, *TravelSmart* increased the walking time by about 3.18 min, which is equivalent to an increase of 42 % (3.18/7.70) from Wave 1.

The last three columns of Table 5 present the model results estimating the effects of *TravelSmart* on total trip distance by travel mode. The results are similar to the results on trip time. First, *TravelSmart* shows a significant effect on reducing the trip distance by car (VKT). On average, *TravelSmart* reduced car trip distance by about 5.30 km per day in Wave 2, a reduction of approximately 28 % (5.30/19.08) from Wave 1. The magnitude of the effects of *TravelSmart* on VKT detected in our study is somewhat larger than the effects of other programs reported by previous studies: for example, a 21 % reduction of VKT were found in *Travel Blending* program implemented in Adelaide (Ampt and Rooney 1998), a 14 % reduction of VKT were found in *IndiMark* program implemented in Perth (James 1998). However, Table 5 shows the effects of *TravelSmart* on reducing VKT were not significant in Wave 3. Again, this implies that *TravelSmart* may not have continuous and long-term effects on reducing VKT. Further, *TravelSmart* did not have immediate and significant effects on increasing bus and walk trip distances. However, the effects of *TravelSmart* were significant in increasing walking distance in Wave 3. In particular, an increase of 0.39 km (or 55 % = 0.39/0.71) from Wave 1 in walking distance can be attributed to *TravelSmart* program.

Overall, the results presented in Table 5 show the importance of looking at the longer term impacts of the *Travel Smart* program. Reductions in car use appear to arise immediately after 'treatment' by *Travel Smart* but do not appear to be sustained. In contrast, increases in bus and walk activity seems to be time-lagged from 'treatment'. Further data collection would be required to see if these latter changes were sustained or not.

To better illustrate the model results, the predicted values (with the 95 % confidence intervals) of trip time and distance by car and walk in three waves are plotted in Fig. 3, where the distances between the treatment and control group are the effects of *TravelSmart*. Figure 1a, b show the changes of trip distance and trip time by car respectively over time. For the treatment group, both trip distance and trip time declined soon after implementation of *TravelSmart*, and then remain constant between Wave 2 and Wave 3. A different trend is observed for the control group, where both trip distance and trip time increased in Wave 2 and then decreased in Wave 3. These different changes in driving behaviour over time between treatment and control groups do suggest *TravelSmart* makes a

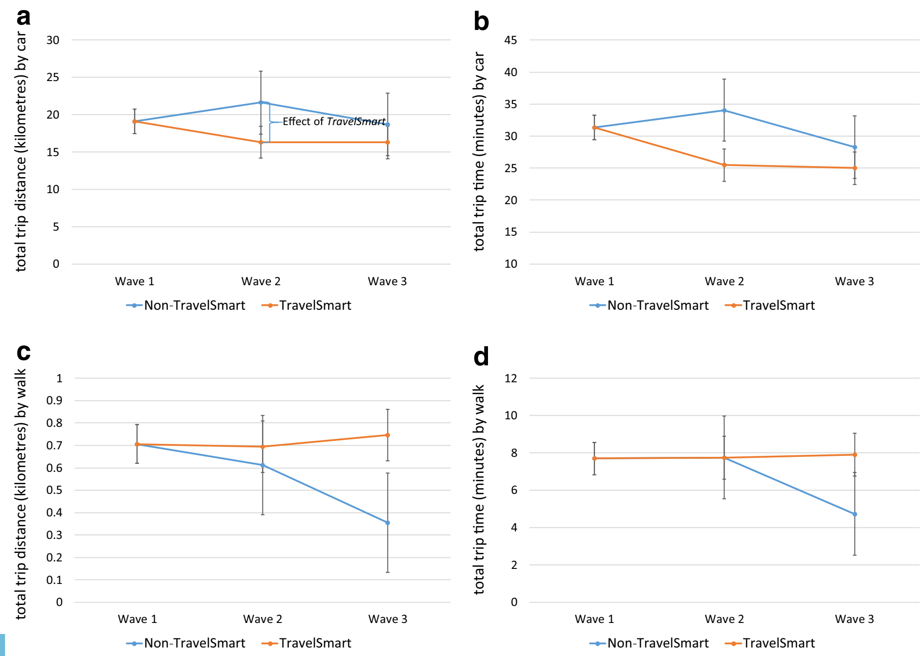

Fig. 3 Predicted travel behaviour changes over time between treatment and control groups

Table 6 Synergistic effects of *TravelSmart* and walkability on travel behaviour change

	Coefficients estimated (absolute value of robust t statistics)								
	Number of trips			Total trip time (min)			Total trip distance (km)		
	Car	Bus	Walk	Car	Bus	Walk	Car	Bus	Walk
Wave 2	−0.38	−0.23	−0.30	−0.12	1.77	−1.14	0.80	1.06	−0.19
	(1.45)	(2.29)**	(2.32)**	(0.03)	(0.65)	(0.71)	(0.26)	(0.78)	(1.18)
Wave 3	−0.74	−0.13	−0.25	−7.49	−2.10	−3.27	−2.72	−0.49	−0.39
	(2.78)***	(1.29)	(1.94)*	(2.12)**	(0.77)	(2.03)**	(0.89)	(0.36)	(2.40)**
Wave 2 × TS	0.05	0.05	0.25	−4.89	−2.14	1.99	−2.93	−1.16	0.26
	(0.14)	(0.43)	(1.64)	(1.17)	(0.66)	(1.04)	(0.81)	(0.72)	(1.36)
Wave 3 × TS	0.48	0.14	0.27	3.14	1.97	3.11	0.66	0.86	0.40
	(1.53)	(1.19)	(1.73)*	(0.75)	(0.61)	(1.62)	(0.18)	(0.53)	(2.09)**
Wave 2 × walkability	0.69	−0.18	0.04	6.42	−10.32	2.74	3.97	−4.51	0.22
	(1.72)*	(1.16)	(0.19)	(1.20)	(2.51)**	(1.12)	(0.86)	(2.20)**	(0.90)
Wave 3 × walkability	1.20	−0.10	0.18	10.11	−4.88	0.69	5.36	−2.06	0.08
	(3.00)***	(0.64)	(0.91)	(1.90)*	(1.18)	(0.28)	(1.16)	(1.00)	(0.34)
Wave 2 × TS × walkability	−0.77	0.12	−0.17	−8.22	10.54	−4.37	−5.26	4.72	−0.39
	(1.65)*	(0.70)	(0.73)	(1.32)	(2.19)**	(1.53)	(0.97)	(1.97)**	(1.36)
Wave 3 × TS × walkability	−1.35	0.03	−0.12	−14.23	4.33	0.08	−6.86	1.62	−0.03
	(2.89)***	(0.14)	(0.53)	(2.29)**	(0.90)	(0.03)	(1.27)	(0.68)	(0.09)
Constant	2.73	0.70	0.79	31.36	14.58	7.70	19.08	7.33	0.71
	(37.65)***	(25.07)***	(22.28)***	(32.38)***	(19.49)***	(17.36)***	(22.69)***	(19.66)***	(15.91)***
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.66	0.62	0.72	0.68	0.55	0.78	0.58	0.56	0.75
Observations	537	537	537	537	537	537	537	537	537

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

difference in travel behaviour change. The changes of trip distance and trip time by walking over time are shown in Fig. 1c, d respectively. These are different from the changes observed in driving behavior with the changes walking distance and time not showing significant differences between treatment and control group in Wave 2, immediately after the implementation of *TravelSmart*. However, a significant difference between treatment and control group can be observed in Wave 3, with the treatment group slightly increasing walking distance and time but the control group significantly decreasing walking distance and time.

Does walkability moderate the effects of *TravelSmart* on travel behaviour change?

Following the evaluation of the effects of *TravelSmart* on travel behaviour change, the analysis turned to whether these effects varied among different built environments. In particular, whether the effects of *TravelSmart* were stronger in high walkable neighbourhoods than in low walkable neighbourhoods indicating that synergies existed between the impacts of these two tools of travel demand management. Separate DDD models were estimated using the model specification presented in Eq. (2) for each of the three dependent variables and for each of the three travel modes. The model results are presented in Table 6.

The first three columns of Table 6 present the model results that estimate the synergistic effects of walkability and *TravelSmart* on total number of trips by each travel mode. The key variables of the interest are the DDD estimators, which are the interaction terms between wave, walkability and *TravelSmart*. For the car trips, the model results indicated that those living in a relatively high-walkable neighborhood reduced their cars trips more than those living in a low-walkable neighborhood after participating the *TravelSmart* program. In particular, in high-walkable neighbourhoods, *TravelSmart* reduced the car trips by 0.77 trips in Wave 2 and 1.35 trips in Wave 3, representing a reduction of 28 (0.77/2.73) and 49 % (1.35/2.73) in number of car trips respectively, whereas in low-walkable neighbourhoods, the effects of *TravelSmart* on car trips were not significant. It is also interesting to note that the effects *TravelSmart* in high-walkable neighbourhoods were significant in Wave 3, indicating that *TravelSmart* could have long-term effects on reducing car trips as long as the built environment supports alternative travel to cars. In addition, it is surprising to note that the effects of *TravelSmart* on increasing the trips by alternative travel modes are not significant in high-walkable neighbourhoods.

The three columns in the middle of Table 6 present the model results that estimate the synergistic effects of walkability and *TravelSmart* on total trip time by each travel mode. For the car trips, the model results suggest that total trip time by car was reduced more in high walkable neighbourhoods than in low walkable neighbourhoods after the implementation of *TravelSmart*, but this difference is only significant in Wave 3. In contrast to the results for the number of trips discussed above, significant synergistic effects were also detected for bus trip times, which increased more in high walkable neighbourhoods than in low walkable neighbourhoods after the *TravelSmart* treatment. It is also interesting to note that the overall effects of *TravelSmart* on bus trip time is not significant (see the fifth column in Table 5), but the effects become very significant in high-walkable environments. This suggests the results of Table 5, averaged over all neighbourhood built environments, are masking the potential synergistic opportunities presented by beneficial built-environmental support.

The last three columns of Table 6 present the model results estimating the synergistic effects of walkability and *TravelSmart* on total trip distance by each travel mode. The

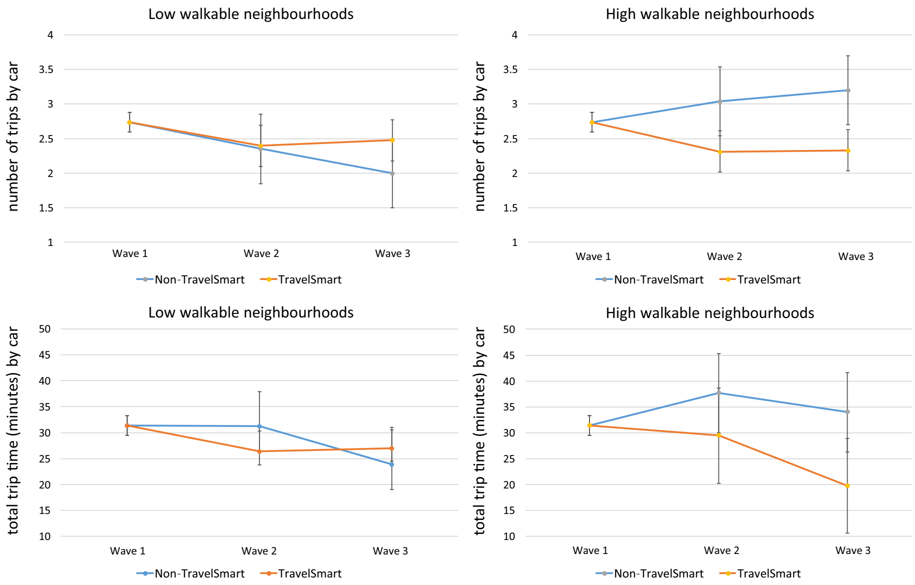

Fig. 4 Different effects of *TravelSmart* on car trips at high and low walkable neighbourhoods

DDD estimators are only significant for bus trip distance in Wave 2, indicating here that total bus trip distance increased more in high walkable neighbourhoods than in low walkable neighbourhoods, after the implementation of *TravelSmart*. However, the overall effects of *TravelSmart* on bus trip distance was not significant (see the eighth column in Table 5). This finding again confirms that a high walkable environment appears necessary for the *TravelSmart* to have positive and significant impacts on bus trips.

The slight differences in model results when using the three dependent variables (number of trips, trip time and trip distance) could result from their different distributions. However, overall model results suggest that *TravelSmart* had stronger effects on reducing the car trips and increasing bus trips in high-walkable neighbourhoods, which also helped the effects of *TravelSmart* to be sustained in the longer term. To better illustrate these model results, changes in car trips (using both number of trips and trip time as dependent variables) from Wave 1 to Wave 3 for both treatment and control group are plotted in Fig. 4. The distances between the treatment and control group in the graphs are the effects of *TravelSmart*. It is clear that the effects of *TravelSmart* are much larger in high-walkable neighbourhoods (two graphs on the right side) than in low-walkable neighbourhoods (two graphs on the left side). In high-walkable neighbourhoods, the effects are sustained or become stronger from Wave 2 to Wave 3.

Conclusions and policy implications

Social marketing and the built environment are soft and hard measures used in managing travel demand. This study contributes by evaluating the relative and combined effects of these two measures on travel behaviour, relying on three-wave panel data collected from 179 persons in 113 households in inner northern Adelaide, Australia.

The empirical analysis suggests that the *TravelSmart* program significantly reduced the car trips soon after the treatment and increased the walking and bus trips 1 year after the treatment. The program appears also to have stronger effects on travel behaviour change for the participants living in high-walkable neighbourhoods than for those living in low-walkable neighbourhoods. Further, *TravelSmart* had longer term effects on reducing car trips in high-walkable neighbourhoods. These findings imply that a high walkable environment that supports alternative travel to cars and social marketing programs could act synergistically so that the combined effect is larger than the effect of each tool when used separately.

Given 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, can be implemented on a monthly or yearly basis as it appears the impact on reductions in car VKT is more immediate than the take up of the alternative modes of bus and walking.

Further, the synergetic effects of social marketing with high walkable neighbourhood environments, featuring relatively high density, connected streets, mixed land-use and good accessibility, suggest that social marketing in these areas could lead to successful reductions in reducing car trips which could be sustained into the longer term. 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 and a further wave or waves of data collection are needed to see if the changes in bus and walking behaviour are sustained or not. Second, 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 discussed to show how the built environment and social marketing might be mutually self-reinforcing, 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 an avenue to understand the mechanism of behaviour change. Although data dependent, a comparison of the effects of social marketing programs implemented in the different cities of Australia would also be enlightening. Further, our sample is based on the single respondents that make up a household and the individuals within the same household are not independent: this may underestimate the standard errors (Cameron and Miller 2015). 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. Finally, because the individuals in our control group also lived in target area, their travel behaviour might be influenced by a friend or neighbour who participated in the *TravelSmart*. This diffusion effect would lead to an underestimation of the effects of *TravelSmart*.

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