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Social marketing and the built environment: What matters for travel behaviour change?

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Social marketing and the built environment: What matters for travel behaviour change?

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 one 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.

KEY WORDS: Social Marketing; Built Environment; Travel Behaviour; Difference-in-Differences

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1. 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 measure. 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
allows 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.

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 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 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, 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, a program similar to the TravelSmart concept in 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 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 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 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 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

3.1 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. Between 2012 to 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; Stopher et al., 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 was 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 one 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.

3.2 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, 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.

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 (Duncan et al., 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.

### 3.3 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 1 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.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Non-TravelSmart (n=96)</th>
<th>TravelSmart (n=245)</th>
<th>p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>48.96</td>
<td>50.57</td>
<td>0.47</td>
</tr>
<tr>
<td>% Female</td>
<td>53%</td>
<td>55%</td>
<td>0.78</td>
</tr>
<tr>
<td>Household size</td>
<td>2.88</td>
<td>2.82</td>
<td>0.77</td>
</tr>
<tr>
<td>#Vehicles</td>
<td>2.01</td>
<td>2.10</td>
<td>0.46</td>
</tr>
<tr>
<td>#Bikes</td>
<td>1.93</td>
<td>1.71</td>
<td>0.38</td>
</tr>
<tr>
<td>Walk Score</td>
<td>55.06</td>
<td>53.79</td>
<td>0.53</td>
</tr>
</tbody>
</table>

The sample characteristics between the three waves were also compared and results are presented in Table 2. 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
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not cause serious attrition bias.

<table>
<thead>
<tr>
<th>Table 2 Characteristics of Sampled Households from Wave 1 to Wave 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<tr>
<td>Age</td>
</tr>
<tr>
<td>% Female</td>
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<tr>
<td>Household size</td>
</tr>
<tr>
<td>#Vehicles</td>
</tr>
<tr>
<td>#Bikes</td>
</tr>
<tr>
<td>Walk Score</td>
</tr>
</tbody>
</table>

3.4 Modelling methods
The first objective of this paper is to evaluate the effects of TravelSmart on travel behaviour change.

The travel behaviour was measured using three dependent variables: number of trips per day, total trip time per day (minutes), and total trip distance per day (kilometres). The descriptive analysis of each dependent variable at each wave is provided in Table 3.

<table>
<thead>
<tr>
<th>Table 3 Descriptive analysis of the dependent variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Number of car trips</td>
</tr>
<tr>
<td>Number of bus trips</td>
</tr>
<tr>
<td>Number of walk trips</td>
</tr>
<tr>
<td>Car trip time (minutes)</td>
</tr>
<tr>
<td>Bus trip time (minutes)</td>
</tr>
<tr>
<td>Walk trip time (minutes)</td>
</tr>
<tr>
<td>Car trip distance (kilometres)</td>
</tr>
<tr>
<td>Bus trip distance (kilometres)</td>
</tr>
<tr>
<td>Walk trip distance (kilometres)</td>
</tr>
</tbody>
</table>

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, before and after the implementation of TravelSmart. DD models for estimating the effect of policy implementation have become very popular in economics and other social sciences (Athey and Imbens, 2002). DD models can rule out all
time-invariant unit-level factors which may not be observable or measurable but may lead to omitted variable bias (Card and Krueger, 1993). Separate models were developed for each of the three travel modes: Car, Bus, and Walk. The DD model is specified as:

\[ y_{it} = \beta_0 + \beta_1 T_{Si} \ast \text{Wave2} + \beta_2 T_{Si} \ast \text{Wave3} + \delta_i + \delta_t + \epsilon_{it} \]  

(1)

Where, \( y_{it} \) represents the three dependent variables for person \( i \) at time point \( t \). \( \beta_0 \) is the constant, which is the mean of \( y_i \) at Wave 1. \( T_{Si} \) is an indicator variable that takes value equal to 1 if individual \( i \) participated in TravelSmart, and 0 otherwise. The individual fixed effects \( \delta_i \) included in the model controls non-parametrically for unobservable individual-invariant characteristics while the time fixed effects \( \delta_t \) controls non-parametrically for yearly differences between outcome values. \( \epsilon_{it} \) is the error term. \( \beta_1 \) and \( \beta_2 \) 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 one year after implementation.

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:

\[ y_{it} = \beta_0 + \beta_1 T_{Si} \ast \text{Wave2} + \beta_2 T_{Si} \ast \text{Wave3} + \beta_3 \text{Wave2} \ast \text{walkability}_{it} + \beta_4 \text{Wave3} \ast \text{walkability}_{it} + \beta_5 T_{Si} \ast \text{Walk2} \ast \text{walkability}_{it} + \beta_6 T_{Si} \ast \text{Wave3} \ast \text{walkability}_{it} + \delta_i + \delta_t + \epsilon_{it} \]  

(2)

Here, \( \beta_5 \) and \( \beta_6 \) are the coefficients of DDD estimators, which test whether the TravelSmart has different effects on travel behaviour change in low and high walkable neighbourhoods.
4. Results and Discussion

4.1 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 equation (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 4.

The first three columns of Table 4 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, $\beta_1$ and $\beta_2$, 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 3 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 3 shows the effects of TravelSmart on increasing bus and walk trips were significant at ten percent level in the Wave 3, which is about one 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 4 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) minutes 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 on car by 2.69 minutes from Wave 1 to Wave 2. 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 minutes (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 minutes, which is equivalent to an increase of 42% (3.18/7.70) from Wave 1.

The last three columns of Table 4 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 kilometres 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 3 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 kilometres (or 55%=0.39/0.71) from Wave 1 in walking distance can be attributed to TravelSmart program.

Overall, the results presented in Table 3 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 seem 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 Figure 1, where the distances between the treatment and control group are the effects of *TravelSmart*. Figure 1a and 1b 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 difference in travel behaviour change. The changes of trip distance and trip time by walking over time are shown in Figure 1c and 1d 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.
### Table 4 Effects of TravelSmart on Travel Behaviour Change

<table>
<thead>
<tr>
<th></th>
<th>Number of trips</th>
<th>Total trip time (minutes)</th>
<th>Total trip distance (kilometres)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave 2</td>
<td>-0.08 (0.41)</td>
<td>-0.31 (4.09)***</td>
<td>-0.29 (2.93)***</td>
</tr>
<tr>
<td>Wave 3</td>
<td>-0.21 (1.06)</td>
<td>-0.17 (2.30)***</td>
<td>-0.17 (1.79)*</td>
</tr>
<tr>
<td>Wave 2 x TS</td>
<td>-0.30 (1.27)</td>
<td>0.10 (1.16)</td>
<td>0.17 (1.52)</td>
</tr>
<tr>
<td>Wave 3 x TS</td>
<td>-0.12 (0.50)</td>
<td>0.15 (1.70)*</td>
<td>0.22 (1.90)*</td>
</tr>
<tr>
<td>constant</td>
<td>2.73 (37.37)***</td>
<td>0.70 (25.14)***</td>
<td>0.79 (22.29)***</td>
</tr>
<tr>
<td>Individual fixed effect</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Adj.R²</td>
<td>0.65</td>
<td>0.62</td>
<td>0.72</td>
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<td>Observations</td>
<td>537</td>
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</tr>
</tbody>
</table>

* p<0.1; ** p<0.05; *** p<0.01
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Figure 1 Predicted travel behaviour changes over time between treatment and control groups

4.2 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 equation (2) for each of the three dependent variables and for each of the three travel modes. The model results are presented in Table 5.

The first three columns of Table 5 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 5 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 3), but the effects become very significant in high-walkable environments. This suggests the results of Table 3, averaged over all neighbourhood built environments, are masking the potential synergistic opportunities presented by beneficial built-environmental support.

The last three columns of Table 5 present the model results estimating the synergistic effects of walkability and TravelSmart on total trip distance by each travel mode. The 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
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TravelSmart. However, the overall effects of TravelSmart on bus trip distance was not significant (see the eighth column in Table 3). 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 Figure 2. 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.
### Table 5: Synergistic Effects of TravelSmart and Walkability on Travel Behaviour Change

<table>
<thead>
<tr>
<th></th>
<th>Number of trips</th>
<th>Total trip time (minutes)</th>
<th>Total trip distance (kilometres)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave 2</td>
<td>-0.38 (1.45)</td>
<td>-0.23 (2.29)**</td>
<td>-0.30 (2.32)**</td>
</tr>
<tr>
<td>Wave 3</td>
<td>-0.74 (2.78)***</td>
<td>-0.13 (-0.13)</td>
<td>-0.25 (1.94)*</td>
</tr>
<tr>
<td>Wave 2 x TS</td>
<td>0.05 (0.14)</td>
<td>0.05 (0.43)</td>
<td>0.25 (1.64)</td>
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<tr>
<td>Wave 3 x TS</td>
<td>0.48 (1.53)</td>
<td>0.14 (1.19)</td>
<td>0.27 (1.73)*</td>
</tr>
<tr>
<td>Wave 2 x walkability</td>
<td>0.69 (1.72)*</td>
<td>-0.18 (-0.18)</td>
<td>0.04 (1.16)</td>
</tr>
<tr>
<td>Wave 3 x walkability</td>
<td>1.20</td>
<td>-0.10 (-0.10)</td>
<td>0.18 (0.19)</td>
</tr>
<tr>
<td>Wave 2 x TS x walkability</td>
<td>-0.77 (1.65)*</td>
<td>0.12 (0.70)</td>
<td>-0.17 (0.73)</td>
</tr>
<tr>
<td>Wave 3 x TS x walkability</td>
<td>-1.35 (2.89)**</td>
<td>0.03 (0.14)</td>
<td>-0.12 (0.53)</td>
</tr>
<tr>
<td>constant</td>
<td>2.73 (37.65)***</td>
<td>0.70 (25.07)***</td>
<td>0.79 (22.28)***</td>
</tr>
<tr>
<td>Individual fixed effects</td>
<td>Yes</td>
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<table>
<thead>
<tr>
<th>Adj. $R^2$</th>
<th>0.66</th>
<th>0.62</th>
<th>0.72</th>
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<td>537</td>
<td>537</td>
<td>537</td>
<td>537</td>
<td>537</td>
</tr>
</tbody>
</table>

* $p<0.1$; ** $p<0.05$; *** $p<0.01$
Figure 2 Different effects of TravelSmart on car trips at high and low walkable neighbourhoods
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5. 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 one 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
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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 (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 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. 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.
References


Stopher, P.R., Moutou, C.J., Liu, W., 2013. Sustainability of Voluntary Travel Behaviour Change Initiatives—a 5-Year Study.