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How the success of social marketing program outcomes can be affected by socio-demographics and the built environment: a multiple group latent growth curve modelling exploration

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TITLE: **How the success of social marketing program outcomes can be affected by socio-demographics and the built environment: a multiple group latent growth curve modelling exploration**

ABSTRACT: Urban sprawl is pervasive in Australian cities arising from the low density development of dwellings. One of the consequences of this is that private vehicle use dominates daily travel in Australia. Reducing car travel by reducing VKT is a target of many transport demand management policies of which community based social marketing programs are proving increasingly popular and effective. Relying on 3-year panel data collected in Australia using both GPS and a normal travel survey in northern Adelaide, South Australia, this paper employs latent growth curve models to evaluate the long-term effects of the social marketing program TravelSmart. The paper explores whether travel behaviour change varies among individuals with different socio-demographic characteristics and among individuals living in different types of neighbourhood. This paper shows TravelSmart had a significant effect on reducing car travel with effects being sustained beyond one year and up to two years. In addition, the paper shows the effects of TravelSmart on reducing the driving varies among individuals with different socio-demographic characteristics and living in neighbourhoods with different levels of walkability.

KEY WORDS: social markeing; built environment; travel behaviour; latent growth model

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1. Introduction

Urban sprawl is pervasive in Australia cities arising from the low density development of dwellings. One of the consequences of this is that private vehicle use dominates daily travel in Australia as demonstrated by recent statistics (BITRE, 2014) which identify private road vehicles accounting for approximately 86 percent of the aggregate passenger task within the Australian capital cities. Overall, the transport sector accounts for 16 percent of Australia's greenhouse gas emissions, and within this light vehicles contribute 57 percent. As importantly, car use is also associated with series of negative personal effects, such as obesity and other health problems related to sedentary lifestyles (Bassett Jr et al., 2008; Ding et al., 2014). Reducing car travel by reducing VKTis a target of many transport demand management policies of which community based social marketing programs are proving increasingly popular and effective.

The approach of community-based social marketing programs is originally developed by a social psychologist (McKenzie-Mohr, 2013), and used by planners to promote sustainable environmental and travel behaviour. Whilst conventional planning tools focus on changing the land use by planning regulations, social marketing programs aim to change behaviour primarily through affecting intra-personal factors such as attitudes, perceptions and norms (Bamberg et al., 2011; Dill and Mohr, 2010). These social marketing programs typically use voluntary action and incentive approaches to change behaviour. In policy terms, social marketing programs are regarded as 'soft' measures and have been extensively used to influence travel demand in many cities worldwide.

Several previous studies have evaluated the effect of social marketing on reducing the car travel and most of these have confirmed the effectiveness of social marketing program in travel demand management. For example, from the early 1990s, Brög (1998) undertook a series of experimental projects to examine the effectiveness of an individualised marketing program approach on public transport use in 13 European countries: he found the use of public transport increased quickly in nearly all projects after the individualized marketing program and without making any system improvements to the public transport itself. Rose and Ampt (2001) evaluated two early trial projects known as *Travel Blending* conducted in Australia, one in Sydney and the other in Adelaide. Their qualitative analysis of the 50 participants in Sydney found an increased awareness of the environmental consequences of using private cars with good intentions displayed by participants to reduce their car travel. The quantitative analysis of the 100 households in Adelaide found about a 10% reduction in vehicle kilometres travelled. Dill and Mohr (2010) examined the effects of City of Portland's *SmartTrips* program in three different neighbourhoods of Portland, Oregon: they found the effects of *SmartTrips* did last beyond one year and up to a least two years but the effects were not significant in one suburban neighbourhood which had less good walkability than the two neighbourhoods where positive effects were achieved. However, there are several studies which have found the effects of the social marketing are not sustained in the long-term. James et al. (1999) evaluated the effects of the *IndiMark* program implemented in Perth, Australia finding the initial changes were not sustained after 12 months. In Taylor's review (2007) of soft transport policy measures implemented in Nottingham, Leeds and Santiago, he also concluded that the trials of Voluntary Travel Behavior Change Programs (VTBC) which showed short-term benefits did not show lasting changes in the travel behaviour of participants.

A review of social marketing programs and their effects on travel behaviour change over the three continents of Europe, Australia, and North America by Brög et al. (2009) found only two studies monitoring the long-term effects of behaviour change and that most evaluation studies undertook pre- and post- surveys with the post-surveys being conducted immediately following the project. A much more recent review by Richter et al. (2011) also 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. This review also identified, as a priority for future research, the need to investigate how hard transport policy measures might increase the effectiveness of soft transport policy measures. In the context of social marketing programs this means investigating whether there are different impacts on different target groups in different locations since the review already shows that soft transport policy measures have different impacts on different target groups. Looking in future research as to how individual differences might impact on travel behaviour is a further implication of this review.

Empirical studies evaluating the effects of social marketing programs on travel behaviour change are limited and they have provided mixed results. In addition, 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. In particular, none of the previous studies have looked at the individual variations in travel behaviour change in response to the social marketing program. Specifically whether an individuals' social-demographic characteristics and their living environment influences the changes of travel behaviour is a gap in the literature. Understanding the factors that influence the effects of a social marketing program is important for future program design and policy implications.

This paper relies on 3-year panel data collected in Australia using both GPS and a normal travel survey in northern Adelaide, South Australia. The social marketing program introduced to participants was called *Travel Smart* and was a voluntary program introduced in many of the Australian states (and is further described below). This paper aims to fill the following research gaps by answering the following three questions: (1) Does *TravelSmart* reduce car travel in the long-term? This is a complicated question and this paper looks at individuals and household responses to the *TravelSmart* program to see whether there is compensatory behaviour intra-household. (2) Does an individual's socio-demographic characteristics influence the effects on the social marketing program on travel behaviour change? (3) Does the built environment make a difference in the effects of the social marketing program on travel behaviour change?

2. Data and Methods

2.1 Data

TravelSmart, a voluntary travel behaviour change initiatives was introduced as a social marketing program by a number of localities around Australia from 2000 onwards. The program provided information to participant households about their travel options: the intention was that households would voluntarily reduce their car use, either by ride sharing, or by using public transport, bicycling, or walking. The details of the specific TravelSmart approach of South Australia can be found in Governemtn of South Australia (2009).

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) between 2012 to 2014. GPS records were collected for all individuals in the household aged over 14 through the carrying of a portable GPS device for a period of 15 days during March-May for each year of the three years. This provides three waves of GPS panel data which is enhanced by the information provided by a paper based questionnaire.

The first wave of data collection commenced in March 2012 from a random sampling of the driver license listings, and randomly generated telephone numbers. 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 second wave of data were collected immediately after the implementation of the TravelSmart instruments and the third and final wave approximately one year later. Table 1 gives a summary of the recruitment process and shows details of the panel data for this study, showing the levels of attrition over the three years. In summary, the panel consists of 144 individuals with valid data for each of the three waves of data collection.

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

2.2 Measures

Outcome variable

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. It should be noted that the detection of a car trip cannot distinguish between a car trip as a driver or as a passenger: not being able to distinguish between these is a common limitation of GPS based data collection. Following the mode detection, the time and distance by each mode were calculated for each person and by each wave to provide the panel data. The principle objective of TravelSmart is to reduce the car travel, thus this study uses as the outcome variables the trip time and trip distance by car.

Socio-demographic variables

The paper questionnaire completed by each participant provides the source of the socio demographic characteristics. Table 2 provides the basic description of the sample. The sample is not truly representative since it was drawn predominantly on listed telephone numbers and driving licence listings. For these reasons it is important to be cautious in transferring the findings of this study to other areas.

Table 2 Sample characteristics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Age	177	49.6	17.9	7	83
Gender (1= female)	177	58%		0	1
% Hold driver licence	177	91%		0	1
# People	179	2.8	1.5	1	8
# Vehicles	178	2.1	1.0	0	6
# Bikes	149	1.7	1.8	0	6

Walkability

The built environment around each participant's home was measured using Walk Score. The 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 neighbourhood) to 88 (very walkable neighbourhood), suggested significant variations of the built environment among the households in the sample. The walkability score was then dichotomized into two groups using a median split to give individuals in high walkability and low walkability neighbourhoods.

2.3 Modelling methods

The methodology involves the estimation of a latent growth model (LGM) first to investigate whether travel behaviour changed after the intervention of TravelSmart. LGM is a flexible latent variable technique that that allows for the estimation of inter-individual variability in intra-individual patterns of change over time (Chan, 2003; Curran et al., 2010). LGM also allows an exploration of the factors contributing to any identified patterns of change through the estimation of the association between these patterns and time-invariant or time varying variables (Chan, 2003). LGM has been widely used in the analysis of longitudinal data in social and behavioural research (Laird and Ware, 1982; McArdle and Nesselroade, 2003; Zhang, 2013). Compared with conventional longitudinal models, such as repeated measures analysis of variance and multivariate analysis of variance, LGM is very flexible in terms of its ability to include a variety of complexities including partially missing data, non-normal distributed measures, complex nonlinear trajectories (Curran et al., 2010) with high levels of statistical power (Muthén and Curran, 1997). In this way the LGM resembles the classic confirmatory factors analysis, where observed repeated measures are incorporated as multiple indicators on one or more latent factors to characterize the unobserved growth trajectories (Curran et al., 2010; Duncan and Duncan, 2004).

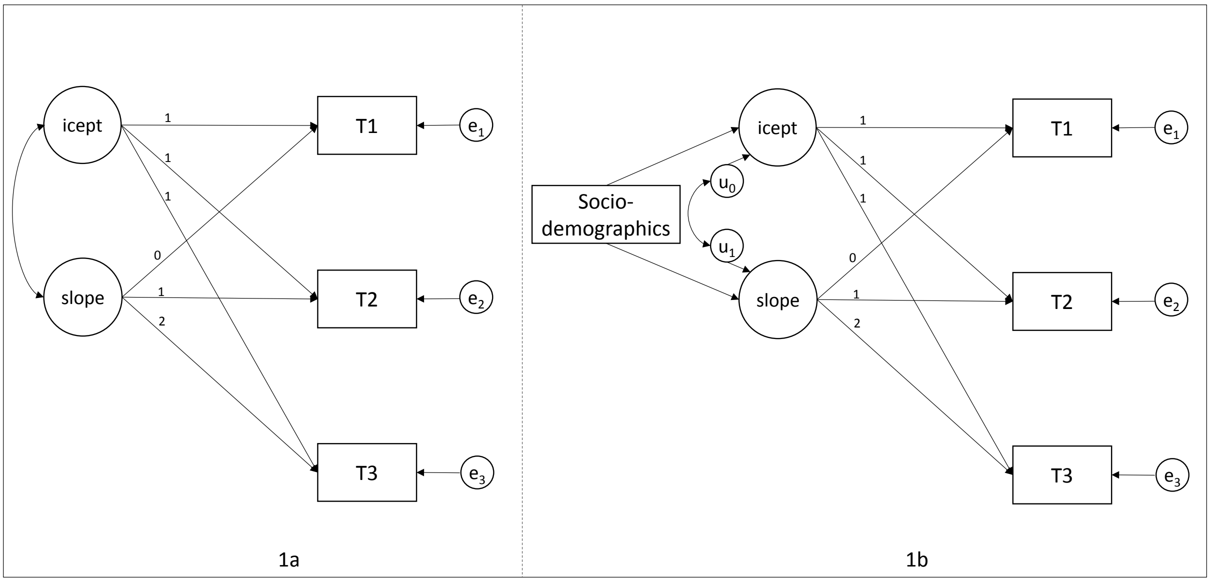

Figure 1: Modelling Frameworks with two parameters, intercept and slope (1a) and a conditional growth model with covariates (1b).

The model depicted in Figure 1a represents the basic form of a LGM in which two parameters, the intercept (representing initial status) and slope (representing rate of change) together describe a linear pattern of intra-individual change over the three time periods, T1 to T3. T1 to T3 are the observations of the response variables which in this paper are the different travel behaviours measured at the three points of time. The intercept is constant over time, modelled by constraining the loadings of all time points on the intercept factor to be equal to one. The latent slope factor is the slope of a linear curve, modelled by constraining the loadings of the three time points to be equal to 0, 1, and 2 respectively. The successive loadings for the slope factor define the slope as the linear trend over time (Hox et al., 2010).

The basic LGM model can be expanded to include one or more predictors of growth. The LGM with covariates is often called a conditional growth model because the growth trajectories are now conditioned on the predictors (Curran et al., 2010). In this study, for example, the socio-demographic characteristics of the participants could influence both the initial status of travel behaviour (shown by the intercept) and rate of changes in travel behaviour (shown by the slope). The socio-demographic variables are, therefore, incorporated as covariates in the LGM model to predict intercept and slope factors (Figure 1b). The conditional LGM specified as Figure 1b aims to test whether the rate of change in travel behaviour (slope) and initial level of travel behaviour is attributable to participants' social-demographic characteristics.

To explore whether Travel Smart influenced travel behaviour through its intervention, and the synergistic effects of social marketing and the built environment on travel behaviour change, multiple-group LGM models were estimated. For this first question, the dummy variable, TravelSmart, is used as the grouping variable to see if the trend in travel behaviour change is different for TravelSmart participants (TS group) and non-TravelSmart participants (Non-TS group). For the second question, walkability (1=high walkable, 0=low walkable) is used as the grouping variable to see if the trend in travel behaviour change is different for high-walkable neighbourhoods compared to low-walkable neighbourhoods. The underlying hypothesis is that residents in high-walkable neighbourhoods are more likely to switch their travel modes from cars to alternative modes after the TravelSmart intervention and therefore more likely to reduce car travel than those living in low-walkable neighbourhoods. Moreover, it is expected that high-walkable neighbourhoods will give rise to a steeper trajectory of change than residents located in low walkable neighbourhoods. With this modelling approach, the multiple-group latent growth model simultaneously fits latent growth models to high-walkable and low-walkable groups.

All the analysis were conducted at both individual and household level. This was to explore the hypothesis as to whether there is compensatory behaviour being undertaken within a household with the reduction of car trips of one member of the household perhaps leading to more trip chaining or activities being undertaken by different members of the household whose car travel may increase. Identifying whether household behaviour change may be different from the travel behaviour change of the individual is important for a wider exploration of the possible synergistic effects of social marketing programs and the built environment.

3. Results and Discussion

In total, six models were estimated using Mplus 7.4. The first two models are basic LGM models estimated at both individual and household level, aiming to investigate how the travel behaviour changed after the TravelSmart, the second two models are conditioned LGM models with socio-demographic covariates estimated at both individual and household level, aiming to answer whether socio-demographic characteristics influence travel behaviour change. The final two models are multi-group LGM models using walkability as the grouping variable, again estimated at both individual and household levels, aiming to explore whether the travel behaviour change is different in high-walkable neighbourhoods as compared to low-walkable neighbourhoods. All the six models fit the data well (Table 3): this is measured by two goodness of fit indices Comparative Fit Index (CFI) and Standardized Root Mean Square Residual (SRMR). Based on Hu and Bentler (1999), who suggest a cut-off value close to 0.95 for CFI and a cut-off value close to 0.08 for SRMR, Table 3 shows a relatively good fit between the hypothesized model and the observed data. Table 3 also reports a χ^2 value since in these type of analyses it is typically reported but it is not really an appropriate measure of model fit as it is sensitive to sample size and several other conditions.

Table 3 Model fit indices

	$\chi2$	df.	p-value	CFI	AIC	SRMR	No. obs.
Multi-group (TS vs. Non TS) LGM (Individual level)	9.044	2	0.011	0.949	4534.294	0.057	179
Multi-group (TS vs. Non TS) LGM (Household level)	8.831	2	0.012	0.961	2915.461	0.092	104
Conditioned LGM (Individual level)	8.884	3	0.031	0.952	3253.516	0.033	128
Conditioned LGM (Household level)	3.206	3	0.361	0.998	1766.102	0.021	64
Multi-group (Walkable vs. Non walkable) LGM (Individual level)	5.206	2	0.074	0.968	3320.398	0.044	131
Multi-group (Walkable vs. Non walkable) LGM (Household level)	3.769	2	0.152	0.986	2164.110	0.036	77

3.1 The effects of the TravelSmart on travel behaviour change

To investigate effect of the TravelSmart on travel behaviour change, multi-group latent growth curve models were tested at both individual and household level. The model results are reported in Table 4. The average baseline driving time for TS group was slightly higher than that for Non-TS group at both individual (32 vs. 26 minutes per day) and household level (53 vs. 41 minutes per day). For both groups, there were significant variability in these driving times shown by the variances across individuals (Non-TS: ψ_{00} = 266.944, p < .005; TS: ψ_{00} = 277.550, p < .005) and across households (Non-TS: ψ_{00} = 2222.288, p < .005; TS: ψ_{00} = 1082.102, p < .005) at the baseline. On average, for TS group, the driving time declined by 3 minutes for individuals and 7 minutes for households each year shown by the means, and this decrease is statistically significant for both the individual level (unstandardized α_1 = -3.027, p<.005) and the household level (unstandardized α_1 = -6.504, p<.005). For Non-TS group, however, the decrease of the driving time was not statistically significant for both the individual level (unstandardized α_1 = -1.002, p=ns) and the household level (unstandardized α_1 = -0.783, p=ns). For TS group, slopes did not significantly vary at both individual (ψ_{11} = 22.781, p=ns) and household level (ψ_{11} = 57.136, p=ns), suggesting that all individuals and households changed over time at approximately the same rate. For Non-TS group, however, slopes vary significantly at both individual (ψ_{11} = 70.770, p<.05) and household level (ψ_{11} = 470.094, p<.05), suggesting that all individuals and households changed over time at different rate. For TS group, the correlation between intercept and slope at individual level was not significant (ψ_{01} = -49.330, p =ns), however, there was a marginally significant negative correlation between baseline scores and slopes at the household level (ψ_{01} = -185.790, p < .1), indicating that households with higher driving time at the beginning of the study were more likely to experience decline in driving time over time. For Non-TS group, there was a significant negative correlation between baseline scores and slopes at both individual (ψ_{01} = -102.260, p <.05) and household level (ψ_{01} = -869.438, p <.05), indicating that individuals and households with higher driving time at the beginning of the study were more likely to experience decline in driving time over time.

The way in which there are similar results from individual and household level estimations and different trajectories of driving behaviour change between TS and Non-TS groups confirm that driving time decreased after the TravelSmart intervention. Further, it is also worth noting that the average rate of decreasing in driving time for each individual calculated based on household level estimation (by dividing the slope of household by the average household number (-6.504/2.8=-2.32)) is lower than that estimated from the individual level model (-3.03), suggesting that 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.

Table 4 Multi-group (TS vs. Non-TS) LGM model results

Individual Level							
		Non-TravelSmart			TravelSmart		
Means		Effect	SE	P value	Effect	SE	P value
	Intercept	26.742	2.299	0.000	31.524	1.834	0.000
	Slope	-1.002	1.346	0.457	-3.027	0.935	0.001
Variance							
	Intercept	266.944	88.888	0.003	277.550	60.256	0.000
	Slope	70.770	32.686	0.030	22.781	25.774	0.377
Covariance		-102.260	46.577	0.028	-49.330	32.246	0.126
Household Level							
		Non-TravelSmart			TravelSmart		
Means		Effect	SE	P value	Effect	SE	P value
	Intercept	41.311	6.222	0.000	53.095	4.311	0.000
	Slope	-0.783	2.440	0.748	-6.504	1.734	0.000
Variance							
	Intercept	2222.288	708.830	0.002	1082.102	233.176	0.000
	Slope	470.094	181.061	0.009	57.136	75.030	0.446
Covariance		-869.438	320.393	0.007	-185.790	100.534	0.065

3.2 Role of socio-demographics on travel behaviour change after the TravelSmart

To investigate whether decreases in driving time observed above are moderated by socio-demographic characteristics, conditioned latent growth curve models are tested at both individual and household levels. The model results are reported in Table 5. The socio-demographic variables tested included age, gender, household size, number of vehicles in the household, and the number of bicycles in the household. In the reported model estimation, only the variables that are significant in at least one path estimation are presented: this allowed the models to be parsimonious which in turn improved model fit. The individual-level model results for gender at the mean show females, on average, driving approximately eight minutes less than males at the baseline (β_1=-7.993, p<.05), with decreases in driving time for females over the three years being significantly smaller than the decrease in driving time for males, as shown by the positive association with slope (β_2=3.734, p<.05) and thereby a flatter slope for females. Also, as expected, individuals having more vehicles had higher driving times than others at the baseline (β_3=3.480, p<.05), however, the number of vehicles have an insignificant impact on the decreasing trend over the three years (β_4=-0.325, p=0.70). The model results at the household level indicated that the households with more vehicles drove more at the baseline than other households (β_3=13.027, p<.005), but their changes in driving time over the three years were not significantly different from others (β_4=0.397, p=0.85). It is interesting to note that the households with more bicycles also had higher car driving times at the baseline (β_5=5.573, p<.05), but they exhibited a quicker decline to their driving time than households with fewer bikes (β_6=-2.106, p<.1).

Table 5 Conditioned LGM model results

	Individual level			Household level		
	Effect	SE	P value	Effect	SE	P value
Direct paths from socio-demographics to intercept and slope						
Gender -> Intercept (β_1)	-7.993	3.647	0.028	-	-	-
Gender -> Slope (β_2)	3.734	1.888	0.048	-	-	-
# Vehicles -> Intercept (β_3)	3.480	1.653	0.035	13.027	4.545	0.004
# Vehicles -> Slope (β_4)	-0.325	0.856	0.704	0.397	2.038	0.845
# Bicycles s -> Intercept (β_5)	-	-	-	5.573	2.772	0.044
# Bicycles -> Slope (β_6)	-	-	-	-2.106	1.243	0.090
Means						
Intercept (α_0)	37.064	7.305	0.000	22.519	8.359	0.007
Slope (α_1)	-8.370	3.781	0.027	-5.561	3.748	0.138
Variance						
Intercept (ψ_{00})	277.550	60.256	0.000	1082.102	233.176	0.000
Slope (ψ_{11})	22.781	25.774	0.377	57.136	75.030	0.446
Covariance (ψ_{01})	-49.895	31.940	0.118	-109.359	85.208	0.199

3.3 The effects of walkability on travel behaviour change after the TravelSmart

To investigate whether there are differences in the decrease trajectory of driving times between the walkability of neighbourhoods, a multi-group LGM models is estimated at both individual and household levels. The model results are reported in Table 6. Model results at the individual level show the average baseline driving time was slightly higher and significantly so in high-walkable neighbourhoods (α_0 = 32.808) than in low-walkable neighbourhoods (α_0 = 30.370), and there was significant variability in these driving times across individuals in both types of neighbourhoods as shown by the significant variances in intercept (non-walkable: ψ_{00}=157.022, p<0.01; walkable: ψ_{00}=398.036, p<0.01). On average, the driving time declined by nearly 4 minutes each year in high-walkable neighbourhoods, and this decrease was statistically significant (unstandardized α_1 = -3.992, p<.05). In contrast, for low-walkable neighbourhoods the decline was just over 2 minutes, and this decrease was only significant at the 10% level of significance (unstandardized α_1 = -2.117, p<.1). This suggests that the walkability of the neighbourhood moderates the effects of TravelSmart on travel behaviour change, with faster decreases in driving time over the three years observed in high-walkable neighbourhoods than in low-walkable neighbourhoods. The model results at the household level are very similar to results at the individual level and provide further confirmation of these findings.

Table 6 Multi-group (Walkable vs. Non-walkable) LGM model results

Individual Level

		Non-walkable			Walkable		
Means		Effect	SE	P value	Effect	SE	P value
	Intercept (α_0)	30.370	2.010	0.000	32.808	3.052	0.000
	Slope (α_1)	-2.117	1.161	0.068	-3.992	1.464	0.006
Variance							
	Intercept (ψ_{00})	157.022	60.264	0.009	398.036	109.164	0.000
	Slope (ψ_{11})	29.335	25.689	0.253	13.869	46.067	0.763
Covariance (ψ_{01})		-52.350	33.995	0.124	-42.619	55.944	0.446

Household Level

		Non-walkable			Walkable		
Means		Effect	SE	P value	Effect	SE	P value
	Intercept (α_0)	51.628	6.483	0.000	54.489	5.704	0.000
	Slope (α_1)	-4.938	2.313	0.033	-8.010	2.547	0.002
Variance							
	Intercept (ψ_{00})	1178.874	365.529	0.001	982.296	294.148	0.001
	Slope (ψ_{11})	-6.137	115.666	0.958	114.311	97.611	0.242
Covariance (ψ_{01})		-160.825	152.233	0.291	-205.176	131.171	0.118

4. Conclusions and Policy Implications

Soft policies such as the social marketing program investigated in this paper aim to reduce driving and promote walking, bicycling and public transport use. These programs are increasingly being proposed and implemented across the world to address the challenges of climate change. Evidence from previous social marketing studies are limited by not being able to discuss the long-term effects through lack of data or limited by not taking account of individual differences in response to the social marketing program and the interactive effects of hard and soft policies. This paper uses unique 3-year panel data together with latent growth curve models to evaluate the long-term effects of the social marketing program *TravelSmart*, implemented in Adelaide, South Australia, to explore whether travel behaviour change varies among individuals with different socio-demographic characteristics and among individuals living in different types of neighbourhood.

The latent growth models at both individual and household levels show that both driving time and the driving distances of *TravelSmart* participants have a declining trend over the three years, indicating that *TravelSmart* had a significant effect on reducing car travel with effects being sustained beyond one year and up to two years. This finding is consistent with the few studies that have demonstrated the long-term effects of the social marketing program. However, by comparing the effects of *TravelSmart* at the individual level and household level, there is some evidence of compensatory behaviour between household members, with the reduction of car trips of one member of the household leading to more car trips being undertaken by different members of the household. This may dilute the effects of *TravelSmart* but not to the extent of making the overall effects on reducing driving time and driving distance at the household level insignificant.

Together, these findings provide further evidence to support using social marketing programs as a soft measure to intervene travel behaviour change.

In addition, this paper shows the effects of *TravelSmart* on reducing the driving varies among individuals with different socio-demographic characteristics. In particular, males decrease their driving time or distance faster than females after the intervention of *TravelSmart*, in other words, females are less responsive to the TravelSmart program than males. Interestingly, households with more bicycles showed a quicker decline to their driving time than households with fewer bikes. However, the panel data only allows for limited socio-demographic variables to be included in the analysis. The results in this paper thus provides some preliminary evidence showing how individual differences in response to the social marketing program are important. This suggests that the design of future social marketing programs must pay special attention to specific groups of people in the preparation of material, distinguishing between information given to males and females, for example.

Finally, this study found that people living in neighbourhoods with different levels of walkability show different travel behaviour change trajectories after the intervention of *TravelSmart*. In particular, those living in high-walkable neighbourhoods have a steeper decrease in driving time and distance than those living in low-walkable neighbourhoods. This suggests that the soft policy of social marketing to reduce VKT works better when it has the support of hard policies such as a supportive built environment. Without a neighbourhood environment that provides the opportunity for alternative travel, the effects of social marketing programs of reducing car travel are more limited. This suggests that the design of future social marketing program must pay attention to the location and built environment of the study area in the promotion of a social marketing program.

This paper has several limitations. First, the relatively small sample size limits the robustness of statistical models and maybe there are other variables that would be significant in a larger panel that would allow confirmation and generalisation of the findings from this study. Second, this analysis could only include thevery limited number of social demographic variables collected by *TravelSmart* and more studies are needed to explore the moderation effects of other socio-demographic characteristics on travel behaviour change using social marketing programs.

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