Journal of Choice Modelling, 4(1), pp 44-61
www.jocm.org.uk

A Combined GPS/Stated Choice Experiment to Estimate Values of Crash-Risk Reduction

Simon Fifer [1, *] Stephen Greaves [1, †] John Rose [1, Ŧ]
Richard Ellison [1,§]

[1] Institute of Transport & Logistics Studies, Faculty of Business, University of Sydney

Received July 2010, revised version received November 2010, accepted December 2010

Abstract

This paper details the development and application of a Stated Choice (SC) experiment designed to explore motorists sensitivities to a kilometre-based charging regime focused around crash-risk reduction. Responses are gathered through a SC experiment that pivots off actual driving behaviour collected over a five week period using an in-vehicle Global Positioning System (GPS) device. This provision of greater reality using revealed preference (RP) information ensures that the alternatives in the SC experiment are embedded in reality, providing motorists with a more realistic context for their choices. The study demonstrates with the improved affordability, power and consumer familiarity with GPS devices, the integration of GPS recorded travel information with SC experiments is a now a feasible solution which can help enrich the quality of the reference alternatives in SC experiments in the future.

Keywords: Stated choice, Revealed preference GPS

* Corresponding author, T: +612-93510072 , F: + 612-93510088, simon.fifer@sydney.edu.au
† T: +612-93510078, F: +612-93510088, stephen.greaves@sydney.edu.au
Ŧ T: +612-93510168, F: +612-93510088, john.rose@sydney.edu.au
§ T: +612-93510186, F:+ 612-93510088, richard.ellison@sydney.edu.au

ISSN 1755-5345

1 Introduction

Recent estimates suggest motor vehicle accidents cost the Australian economy around $17 billion per year (Connelly and Supangan 2006). While both the number of crashes and crash rates (crashes/kilometre) has reduced dramatically in the last thirty years, recent statistics show that 1,463 persons were killed on Australian roads in 2008, with 395 killed in the state of New South Wales alone. More worryingly, it appears reductions may have stagnated in recent years, leaving policy-makers searching for other options that might lead to significant drops in crash rates. While engineering-based methods for both roadway infrastructure and vehicles, and regulation and enforcement will continue to play a critical role in future road-safety initiatives, an area of growing interest is whether financial mechanisms that capture the variable risk effects of the kilometres driven can be used to encourage safer driving practices (Litman 2008). The notion here is that through incorporating correlates of increased crash risk (e.g., kilometres driven, night-time driving, speeding, road type) directly into a charging scheme, motorists will be incentivised to change behaviour reducing the overall risk and societal costs of accidents (Zantema et al. 2008).

Arguably, the greatest innovations in this area have come through the commercial sector in the form of PAYD insurance products, in which premiums are differentiated to kilometres driven and in some cases time, location and speed (Litman 2008). The more elaborate schemes have used Global Positioning System (GPS) technology to track motorists and through integration with powerful back-end servers, automate the computation of insurance premiums (Norwich Union 2006). However, the motivations for these schemes are invariably commercial, little detail is provided on how the premiums are established, and while some aggregate indicators of the outcomes of such programs may be provided rarely are details provided on the changes in before and after driving.

Research efforts to understand motorist responses to kilometre-based charging schemes have taken both a hypothetical/stated choice (SC) and/or empirical/revealed preference (RP) approach. The primary focus of these investigations has been congestion mitigation with relatively few focusing on risk reduction per se (Zantema et al. 2008; Nielsen 2004; Reese and Pash-Brimmer 2009). A recent exception to this was conducted in the Netherlands in which SC methods were used to investigate the response of young drivers to various pay-as-you-drive (PAYD) insurance schemes (Zantema et al. 2008). Their conclusion was that a scheme comprising time and road type differentiation could reduce road crashes by five percent. However, no published evidence is available on how this changed behaviour in reality. The few RP investigations that have been done have largely focused on safer driving, primarily speeding (Mazureck and van Hattern 2006; Gunnar et al. 2005). In the Beloniter speed trial conducted in the Netherlands, motorists were paid to stay within the speed limit and maintain a safe following distance from other vehicles on the road (Mazureck and van Hattern 2006). Results indicated that speeding was reduced by around 20 percent based on a reward of 0.04 Euros for every 15 seconds spent not speeding. Notably, once the rewards were removed, drivers largely reverted back to their original behaviour.

Investigations that have combined SC/RP approaches have generally done so by using the SC results to inform the design of the charging scheme used in the RP experiment (Nielsen 2004). However, these SC experiments have generally been framed as choices in hypothetical markets. More recently, there has been a growing body of evidence on the merits of using reference alternatives in SC experiments to try and ground the choice task in a level of realism and relevancy (Gilboa et al. 2002; Starmer 2000). It is argued that the use of reference alternatives will allow the respondent to more easily address the choice task by comparing to a known experience and thereby improve the reliability of the results (Hensher 2010).

Within this context, the current paper reports on a study into the stated response of motorists to a kilometre-based charging regime that incorporates elements of risk, specifically kilometres, night-time driving and speeding. Responses are gathered through a SC experiment that pivots off actual driving behaviour collected over a five week period using an in-vehicle GPS device (Greaves et al. 2010). The use of RP information in this way ensures that the alternatives in the SC experiment are embedded in reality, providing motorists with (in theory) a more realistic context for their choices. In the SC experiment, participants are asked to trade-off financial rewards against reductions in kilometres driven, night-time driving and speeding for different trip purposes. In turn, this information is used to estimate values of crash-risk reduction and help guide a proposed charging regime that will be used to empirically assess changes in behaviour later this year.

The objective of the current paper is to discuss the use of combining GPS data with SC data. In doing so, we report a series of models for various trip purposes estimated on the GPS embedded SC data. Although it is possible to estimate models on the GPS data and compare these results to those obtained from the SC data, we do not do so here. Whilst comparing model results estimated on RP and SC data would allow for a comparison of so called 'hypothetical bias' effects, we avoid such a comparison here as such comparisons represent ongoing research efforts.

The paper is structured as follows. In Section 2, the major phases of the study design are detailed. This covers the GPS data collection required to derive measures of driving behaviour, the rationale and formulation of the charging regime and the design and implementation of the SC experiment. Section 3 presents the SC model results and willingness to pay measures before finally drawing conclusions together in Section 4.

2 Study design

Motorists were recruited initially to undertake a ten week study of driving in Sydney involving both a GPS and online survey component for which they would receive a gift card worth AU$30. Note there was no mention of the potential to make money through changes in driving at the recruitment phase because of the potential for contamination. The study encompassed five distinct phases: a 'before' period of GPS monitoring (GPS 'Before'), establishment of the charging regime, a stated choice survey completed at the beginning of the 'After' phase (SC 'Before'), an 'after' period of GPS monitoring (GPS 'After) and a stated choice survey completed at the end of the 'After' phase (SC 'After) (see Figure 1).

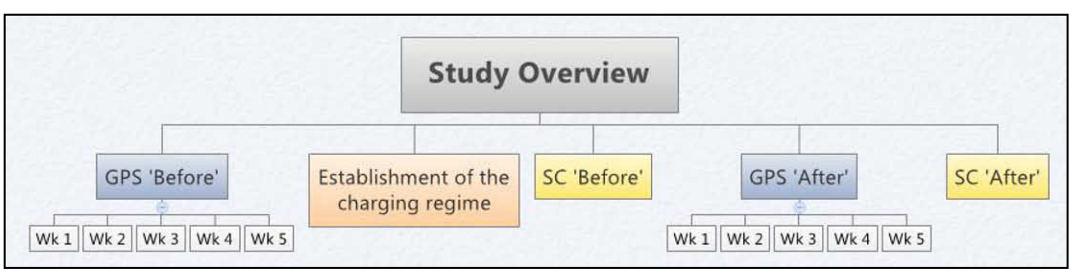

Figure 1. Study Overview

2.1 The GPS 'Before' Phase

Following agreement to participate, motorists were provided with a small GPS device, installed via the cigarette lighter. The device collected key elements (position, time, speed, etc.), which were broadcast back in real-time to servers via General packet radio service (GPRS) where the information was processed into daily trip logs (Greaves et al. 2010). Trip origins were inferred based on when the engine was switched on, while conversely destinations were inferred based on when the engine was switched off. These data were then transformed to provide the basis for an online survey in which motorists were prompted for further information on their trips, including who was driving, the purpose of the trip (e.g., commuting, shopping, social etc.), number of passengers and whether any intermediate stops were made (see Figure 2). Note, that participants were able to provide details of any missing or erroneous trips as part of this process, but they were not expected to manually add/delete/combine trips on-screen mainly because of concerns over the burden of having to do this for several weeks.

In total, 148 motorists were recruited into the GPS-phase of the study. While full details of the GPS phase are provided by the authors (see Greaves et al. 2010), the data were generally of a very high quality. Of the original 148 drivers, only eight dropped out at the 'before' phase, of which four were due to technical problems with the GPS devices not working in their vehicles.

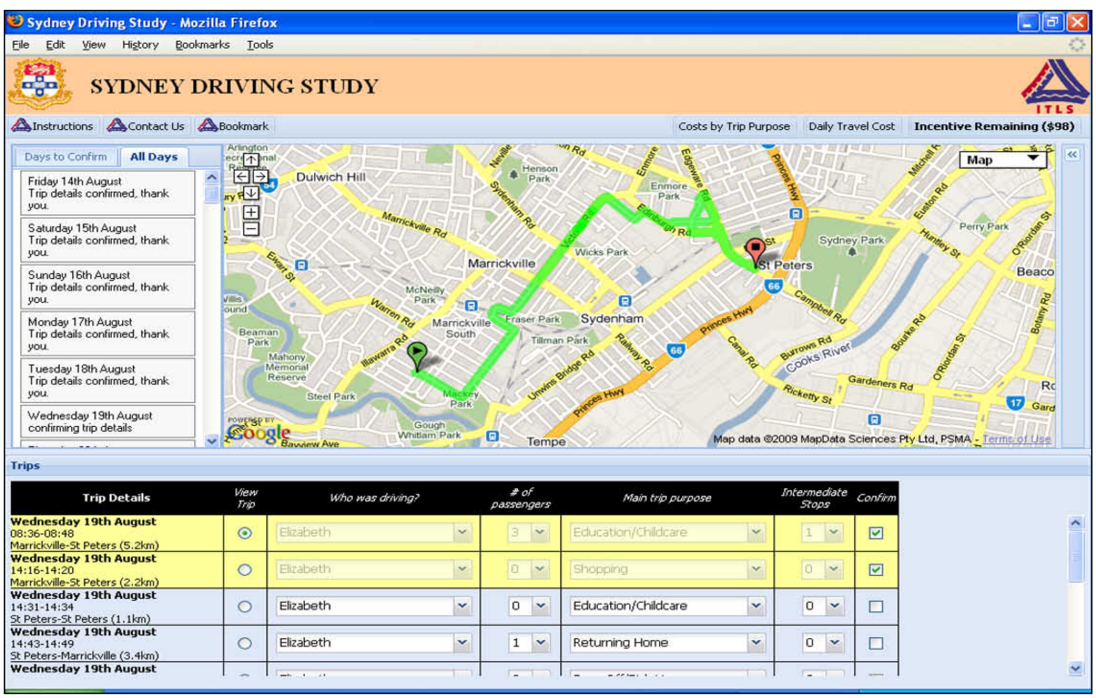

Figure 2. Example of the Prompted-Recall Interface

2.2 Establishment of the Charging Regime

The charging regime was designed to encourage safer driving behaviour by charging motorists according to known correlates of crash-risk (e.g., age, kilometres driven, night-time driving, driving on particular roads, speeding, etc.). The regime used (Table 1) was developed considering the scientific evidence on crash risk, motorist comprehension of the scheme, and *crucially* what rates were deemed sufficient to warrant desired changes in behaviour while staying within the project budget (Greaves and Fifer 2010). In terms of the decision on crash-risk categories, analysis of accident and travel exposure data from New South Wales showed that crash-risk was heavily influenced by age (higher for younger age-groups), time-of-day (higher at night) and speeding – note, road type was also deemed important but rejected as it resulted in too complex a scheme for participants to understand. The actual rates themselves were based on establishing a base rate for the 'safest' situation, namely 'Day – Non speeding', and then applying multipliers to reflect the relative risk of other situations.

Of the 140 motorists who made it through the five-week 'before' period of data collection, 125 qualified for the charging phase (15 were retained as a control group). For these 125 motorists, the range of base incentives ran from AU$25 to AU$915, with an average of AU$300 (see Table 2). For a five-week period, these were considered to be significant amounts of money that could potentially be made.

Table 1. Per Kilometre Charging Regime (Adapted from Greaves and Fifer 2010)

Charging Rates	**17-30 Age-Group**	**31-65 Age-Group**
Day - Non Speeding	$0.20	$0.15
Day – Speeding	$0.60	$0.45
Night - Non Speeding	$0.80	$0.60
Night - Speeding	$2.40	$1.20

Table 2. Driving Characteristics of the Sample and Potential Budgetary Impacts*

Age-Group	Sample	Average Daily VKT**	% Night VKT	% Speeding (Day)		% Speeding (Night)		Starting Budget (based on 5 weeks)	
				Mean	Max	Mean	Max	Mean	Range
17-30 Male	9	24.7	26%	11%	17%	12%	44%	$355	$85-$630
17-30 Female	23	28.4	16%	14%	34%	16%	50%	$405	$105-$815
31-65 Male	47	32.2	12%	13%	44%	13%	45%	$305	$30-$870
31-65 Female	46	26.7	7%	12%	26%	12%	39%	$250	$25-$915
TOTAL	125	29.0	12%	13%	44%	13%	50%	$300	$25-$915

*Maximum budgetary impacts - $35,950
** Vehicle kilometres travelled

2.3 The GPS ‘After’ Phase

The ‘after’ phase involved a further five-week period of GPS monitoring in which the charging regime presented in Table 1 was implemented. The regime was applied by taking the relevant GPS-derived information from the ‘before’ phase for each motorist to establish a ‘base incentive’. This base incentive represented the starting point (i.e., maximum amount they could make) from which money would be deducted according to the kilometres driven, night-time driving and speeding in the five-week ‘after’ phase of GPS monitoring. Motorists were able to log on to the website where they would now see how much of their base incentive they had left (see Figure 3). Any money remaining at the end of the five-week period was paid out to motorists. Note however that respondents did not pay if they exceeded their base incentive.

Preliminary results indicate that around half of the motorists made money (i.e., they reduced kilometres and/or night-time driving and/or speeding relative to their five week before period). For those making money, the average payout was $64 with the highest payout being $563. Vehicle kilometres travelled (VKT) were reduced by eight percent, speeding was reduced by 4.2 percent whilst the proportion of night-time driving marginally increased. In terms of statistical significance, paired sample one-tail t-tests on the total eligible sample indicate that overall changes to VKT ($p<0.03$), and speeding were significant ($p<0.00$), whilst changes to time spent driving at night were not significant ($p<0.19$) at the 95 percent confidence level. Exit interviews with a cross-section of participants highlighted the practical difficulties of reducing kilometres for many participants because of a perceived lack of realistic alternatives to the car. However, (arguably the most encouraging outcome) most participants indicated that it had motivated them to become more aware of and actively their reduce speeding.

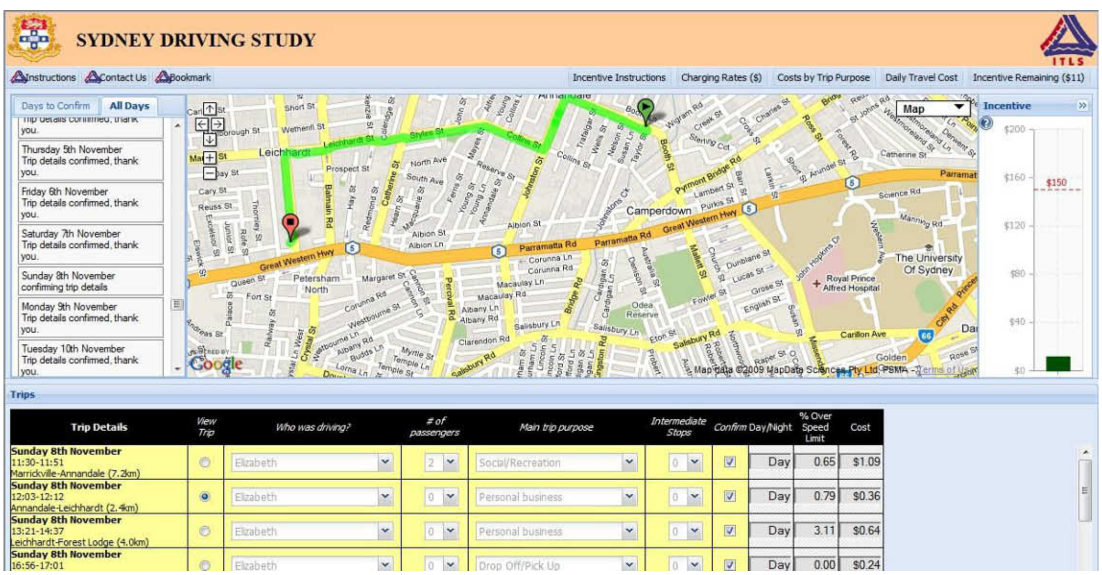

Figure 3. Prompted-Recall Survey Interface (Charging Phase)

2.4 The Stated Choice Experiment

The purpose of the SC experiment in this study was two-fold. First, was the desire to explore how respondents might hypothetically change their driving behaviour if they were participating in a kilometre based rewards scheme to estimate values of crash-risk reduction. Second, was the question of how the SC choices matched revealed preferences, generally referred to as hypothetical bias (Hensher 2010; Harrison 2007). Although the second issue is important, the focus of this paper is purely to address the first issue; the issue of hypothetical bias is complex and will be addressed in future research by comparing the SC results to what happens when the rewards scheme shown in Table 1 are implemented in the field. Unfortunately to attempt to address both issues in a single paper is simply not possible given space limitations, and would detract somewhat from the message of the current paper, that being how GPS technology can be used to assist in constructing SC survey tasks.

The SC experiment was implemented for three different trip purposes; work/work-related business, shopping/personal business, and social/recreation. The experiments were based on a choice between maintaining existing trips (the current alternative) and hypothetical alternatives involving changes to existing trips and receiving a reduced charge (e.g., cancelling trips, reducing speeding, changing time of day). In keeping with recent literature on referencing SC experiments to a known experience (Rose et al. 2008; Rose and Bliemer 2009), the SC experiment was designed to pivot off actual trips taken from the GPS data collected during the five week 'before' period.

The data presented for each alternative was an aggregated summary of driving over a five week period. The use of individual trips was considered for the SC study design but was ultimately rejected because it did not enable an overall comparison of driving changes for a specific trip purpose. That is, other than the work commute, many recorded shopping, personal business, social and recreational trips varied not only by the location visited but also the time of day and observed speeding patterns. To focus on an individual trip to a specific location with only one route and one measurement of time and speeding behaviour would mean that trip would not be able to be generalised to the overall changes that could be made within a given trip purpose.

The integration of the GPS data with the SC experiment required some manipulation, primarily around how to assign VKT to one of the three trip purposes. The main issue here concerned trips that were coded as 'returning home', which constituted around one-third of trips. Geographical information systems (GIS)-based routines were employed to first validate home locations provided by participants (i.e., look for a common location of trips designated as 'returning home') and second reclassify 'returning home' trips based on the primary purpose of the tour. A number of different options were considered for this reclassification, but ultimately the approach taken was to reclassify trips according to that used in the Sydney Household Travel Survey (Transport Data Centre 2007). Under this scheme, if any of the trips in the tour had a purpose of work, work-related business or education then the trips for which the purpose was "returning home" would be reclassified to the appropriate purpose. For tours where this was not the case (such as tours made up of social and shopping trips), the 'returning home' trip would be reclassified to the purpose where the most time was spent during the tour. The purpose of all other trips in the tour remained unchanged.

The choice scenario layout was designed to be simple and intuitive, with the final format decided upon after extensive piloting. A combination of symbols and colours were used to allow the respondent to quickly and easily process the relevant information and make decisions. An example screenshot of a choice situation for social trips is shown in Figure 4. Distance was presented as the total number of kilometres travelled in conjunction with the number of driving days during the five week period and was displayed graphically to facilitate easier comparisons between the alternatives. Both driving time of day and speeding were presented as percentages of occurrence throughout the five week driving period. The attribute travel time, which represents the average increase in travel time per trip, was included in the experiment after much discussion about respondent perceptions of speeding and the likelihood that they would choose the lowest speeding figure without considering any consequences to their daily driving. The charging component consisted of a base incentive, shown to represent the maximum possible amount of money participants could make, and a charge based on driving behaviour. The monetary incentive for participants to change their behaviour was calculated as the base incentive minus the charge. The incentive was structured this way rather than shown directly because this followed the fieldwork charging design.

Choice situations for the other trip purposes were identical to Figure 4, except the colours in the graphs were different. Respondents answered four choice situations for each of the three different trip purposes. Respondents only answered choice questions for the trip purposes which they drove.

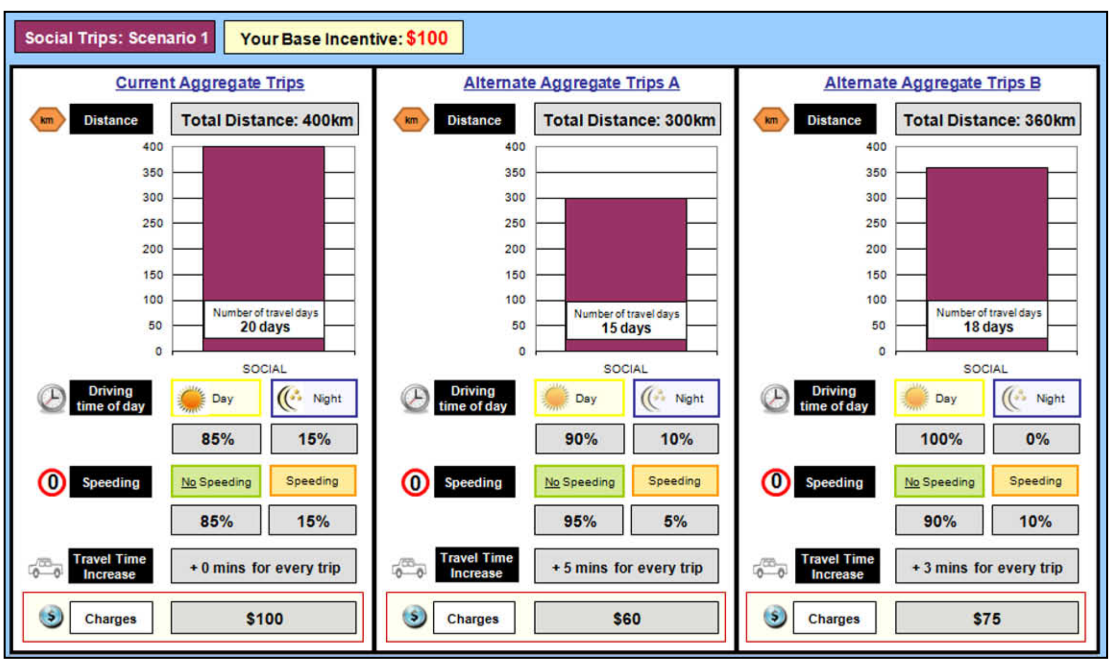

Figure 4. Example Screen from the Stated Choice Survey

2.4.1 Experimental design

A Bayesian efficient design for each trip purpose was generated. This experimental design method was used to produce lower standard errors and provide more reliable parameter estimates for a relatively small sample size (Rose and Bliemer 2009). The experimental designs were constructed in Excel, assuming a uniform distribution of prior parameters, given expected parameters signs. Intuitively the prior parameters for charge and travel time were assumed to be negative, while prior parameters for distance and driving at night were assumed positive. Speeding was allowed to vary from positive to negative due to the possibility that some participants preferred more speeding and some less speeding. Distance was assumed to be positive because respondents would prefer to maintain their level of driving (e.g., any reduction in driving would be considered a burden due to alternative transport arrangements that need to be made and/or activities that would need to be cancelled).The pivot levels for each of the attributes are shown in Table 3. These levels were selected to represent the possible range of driving responses to the charging regime. The number of days travelled was used for pivoting from the attribute distance in order to focus on changes to only whole days of travel. Given the linkage between travel time and speeding, travel time was constrained to be zero when speeding behaviour did not change (i.e., zero percent level).

2.4.2 Implementation

The study was structured so that approximately half the sample completed the SC experiment prior to completing the GPS 'After' fieldwork stage (October 2009), with the other half completing the SC experiment at the completion of the GPS 'After' fieldwork stage (December 2009). This splitting of the sample was designed to test any differences in the order of completion and avoid any associated issues (e.g., do respondents do what they say they will do because they completed the hypothetical survey first). In total, 105 out of the 125 motorists who completed the 'before' GPS

Table 3. Description of Attributes and Pivot Levels

Attribute	Description	Pivot Levels (off the reference level)
Distance	The total number of km you drive. The number of travel days on which that purpose was driven is also shown.	0%, -10%, -25%, -50%, -75%
Driving Time of Day	The percentage (%) of your total driving in the 'Day' (5am - 8pm) and 'Night' (8pm - 5am).	0%, -25%, -50%, -75%, -100%
Speeding	The percentage (%) of your total driving where you are 'Speeding' and 'Not Speeding'.	0%, -25%, -50%, -75%, -100%
Travel Time	The average increase in travel time per trip (in minutes) if you were to reduce your speeding behaviour.	0 mins, 2 mins, 4 mins, 6 mins, 8 mins
Charges	The amount of money you would pay (reduced from your base incentive) to drive for that trip option.	-10%, -20%, -30%, -50%, -75%

data collection phase also completed the SC experiment. The before and after SC samples were intended to be approximately equal. However, during the after phase some participants were unable to complete the study because they went on extended holidays (8 participants) or failed to complete the prompted trip recall (2 participants). This left 115 eligible participants who were sent an email invitation to complete the SC survey. The response rates for the ‘Before’ and ‘After’ phase of the SC experiment were 62 out of 64 (97 percent) and 43 out of 51 (84 percent) respectively. As expected, it proved more difficult to get participants to complete the SC experiment at the end of the study because of the length of the study duration.

The SC survey was administered online and built using PHP, HTML/CSS and a MySQL database. An email was sent to each participant, which contained a personalised link to the online survey. The survey was designed so that the participants could stop the survey at anytime and resume where they finished. An email and phone help line was established to field any problems participants had whilst completing the survey. On average, the survey took approximately 25-30 minutes to complete, with the SC component accounting for the greater part of this completion time. The final sample composition for the participants who completed the SC experiment can be found in Table 4.

2.4.3 Participant Feedback

Participant feedback on the survey was generally positive, with many reporting they found the experiment ‘fun’ and ‘interesting’ although several indicated a difficulty in changing behaviour. Two scales were used to quantitatively measure the survey response. One scale measured the ease of understanding the choice scenario games (where 0 was "Did not understand at all" and 10 was "Completely Understood"). The majority of participants indicated that they understood the task, with a median scale value of eight (Figure 5). The other scale measured the difficulty of completing the choice scenario games (where 0 was "Very Difficult" and 10 was "Very Easy"). Similarly most participants found the choice task relatively straightforward, with a median scale value of seven (Figure 6).

Table 4. Sample Composition (Stated Choice Survey)

Gender	Age	SC Before	SC After	Total
Male	17-30	4	3	7
	31-65	25	16	41
Female	17-30	8	13	21
	31-65	25	11	36

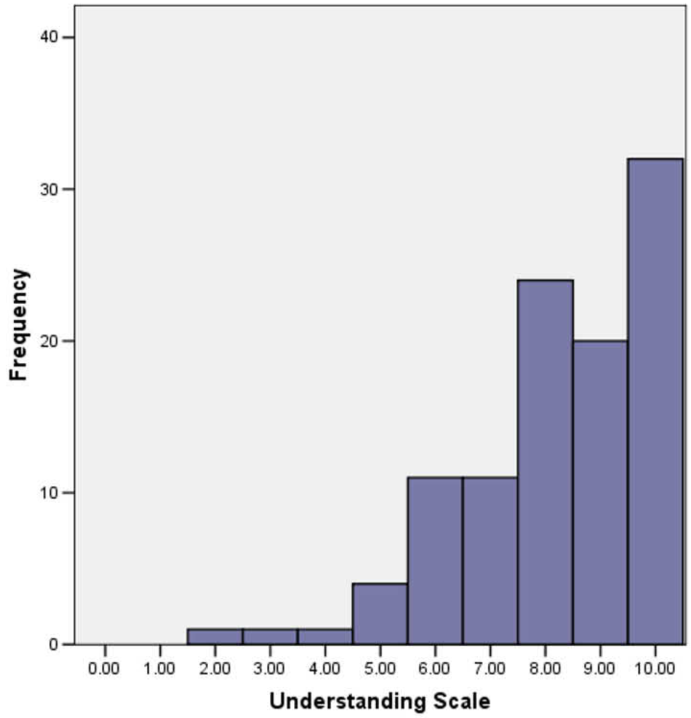

Figure 5. Understanding Scale Distribution

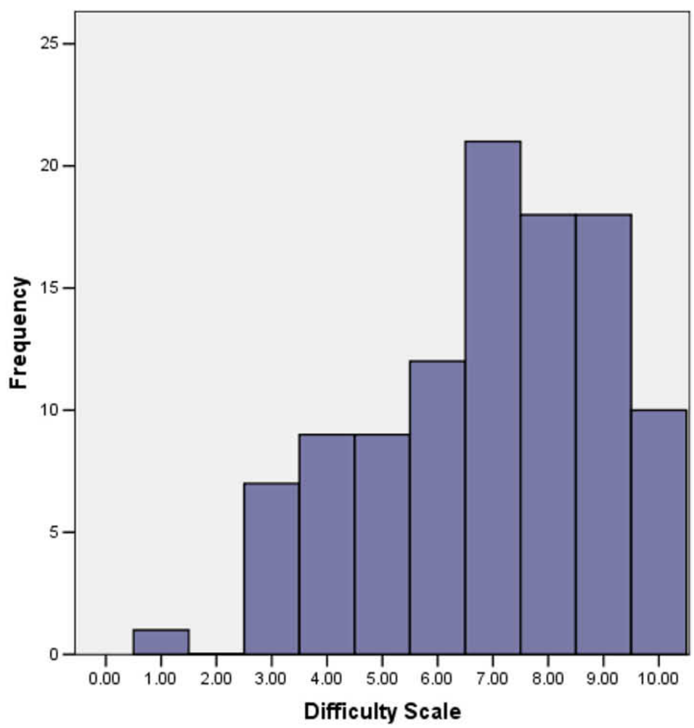

Figure 6. Difficulty Scale Distribution

3 SC Results

The standard 'workhorse' model for choice modelling is the Multinomial Logit (MNL). In keeping with standard notation the utility U_{nsj} can be written as the sum of the observable component (otherwise referred to as the systematic component, V_{nsj}, expressed as a function of the attributes presented (for alternative *j* by respondent *n* in choice situation *s*), and a random or unexplained component, ε_{nsj} as shown in equation (1).

$$U_{nsj} = V_{nsj} + \varepsilon_{nsj} \tag{1}$$

V_{nsj} in its simplest form, is typically assumed to be a linear relationship of *k* observed attribute levels (x) and corresponding parameter weights (β).

$$V_{nsj} = \sum_{K=1}^{K} \beta_{jk}\, x_{nsjk} \tag{2}$$

The MNL has certain restrictive assumptions which have led to the development of more advanced models, including the Mixed Multinomial Logit (MMNL) and Error Components (EC) model. The modelling of the data for this paper will focus on the EC model. The utility U_{nsj} for the EC model includes the estimation of an unobserved component of utility, η_{nsk}. The EC model is similar to the Mixed Multinomial Logit Model (MMNL), except the random parameters are associated with alternative *j*, not attribute *x*. These random variables are represented as η_{nsj} in equation (3). η_{nsj} captures the common error variances in the sets of alternatives constructed. The random parameters for the EC model were estimated using 500 Halton draws. All models were estimated using the software Nlogit 4.0.

$$U_{nsj} = V_{nsj} + \eta_{nsj} + \varepsilon_{nsj} \tag{3}$$

The general EC model utility functions for both the 'Before' and 'After' samples are displayed in equations 4 and 5 respectively.

$$\begin{aligned}
\boldsymbol{U_{Current_Before}} &= ASC_{Current_Before} + \beta_D x_{Distance} + \beta_N x_{Night} \\
&+ \beta_S x_{Speeding} + \beta_T x_{Travel\ time} + \beta_{ST} x_{Speeding*Travel\ time} + \beta_C x_{Charge} \\
&+ \varepsilon_{Current_Before} \\
\boldsymbol{U_{AltA_Before}} &= \beta_D x_{Distance} + \beta_N x_{Night} + \beta_S x_{Speeding} + \beta_T x_{Travel\ time} \\
&+ \beta_{ST} x_{Speeding*Travel\ time} + \beta_C x_{Charge} + \eta_{Before} + \varepsilon_{AltA_Before} \\
\boldsymbol{U_{AltB_Before}} &= \beta_D x_{Distance} + \beta_N x_{Night} + \beta_S x_{Speeding} + \beta_T x_{Travel\ time} \\
&+ \beta_{ST} x_{Speeding*Travel\ time} + \beta_C x_{Charge} + \eta_{Before} + \varepsilon_{AltB_Before}
\end{aligned} \tag{4}$$

$$\begin{aligned}
\boldsymbol{U_{Current_After}} &= ASC_{Current_After} + \beta_D x_{Distance} + \beta_N x_{Night} \\
&+ \beta_S x_{Speeding} + \beta_T x_{Travel\ time} + \beta_{ST} x_{Speeding*Travel\ time} + \beta_C x_{Charge} \\
&+ \varepsilon_{Current_After} \\
\boldsymbol{U_{AltA_After}} &= \beta_D x_{Distance} + \beta_N x_{Night} + \beta_S x_{Speeding} + \beta_T x_{Travel\ time} \\
&+ \beta_{ST} x_{Speeding*Travel\ time} + \beta_C x_{Charge} + \eta_{After} + \varepsilon_{AltA_After} \\
\boldsymbol{U_{AltB_After}} &= \beta_D x_{Distance} + \beta_N x_{Night} + \beta_S x_{Speeding} + \beta_T x_{Travel\ time}
\end{aligned} \tag{5}$$

$+\beta_{ST}x_{Speeding*Travel\ time} + \beta_C x_{Charge} + \eta_{After} + \varepsilon_{AltB\_After}$

Results comparing the basic MNL with an EC model for each trip purpose are presented in Table 5. The EC model was chosen because it is a more flexible and superior model compared to the standard MNL. The EC model allows for repeated choice observations as well as accounting for correlation in the errors of the alternatives. The 'Before' sample and 'After' sample were pooled for analysis. However, separate constants were estimated for the current alternative and also separate error components were estimated for the hypothetical alternatives to account for any error differences between the hypothetical and the reference alternatives across the two samples (Scarpa et al. 2005). An interaction term between speeding and travel time was included to test for any significant relationship between these variables.

The model fit results demonstrate that the EC model provides a better fit to the data than the standard MNL model. Insignificant parameters were removed from the final EC model. For all models the error component (η_{nsk} in equation 3) estimated for the hypothetical alternatives (1 & 2) were significant, highlighting error differences between the hypothetical and the reference alternatives across the two samples. Results from the work trip purpose model suggest that participants were mainly concerned with the ability to drive and were reluctant to change. Interestingly participants also preferred driving options with less speeding irrespective of any time penalties incurred. These results are in line with anecdotal evidence gathered during pilot interviews which revealed that the work commute would be the least likely trip purpose to be altered during the charging phase. All parameters for the social/recreational trip model were significant and of the expected signs. The interpretations for the distance and speeding parameters are the same as for work trips, namely that participants prefer to use their car to drive to social/recreations activities and also desire to speed less. As might be anticipated, participants prefer to maintain their night driving for social/recreation trips and are more travel time sensitive (i.e., they dislike extra travel time per trip). Unlike work trips, the charging regime had a significant impact on driving choices for social/recreations trips. Participants preferred to choose trips options with lower charges and were willing to change some of their current driving behaviour to reduce the charges and hence make some money. Similar significant results were achieved for the shopping model with the exception of driving time of day and travel time. The negative sign for the alternative specific constants for the current alternative suggests that in most models participants were less likely to choose the current alternative and favoured the hypothetical alternatives ceteris paribus.

Willingness to Pay (WTP) measures were computed to further understand and compare the impact each attribute has on behavioural change and the relationship with the charging regime. WTP is simply the marginal utility of a particular attribute divided by the marginal utility of the charge (i.e., the ratio of the two coefficients) and enables comparison across models because they are not influenced by the scale factor. WTP calculations for social/recreational trips and shopping/personal business trips are shown in Table 6 and Table 7 respectively. WTP values for work trips are not presented because the charge parameter was not significant. Confidence intervals were calculated using the Delta method (Greene 2000). For social/recreational trips participants were on average willing to pay $0.53 for an additional kilometre of travel. The importance of night driving for social/recreational trips is highlighted in the high WTP value. Participants were willing to pay $3.54 for an additional percentage of

Table 5. Model Results

	Work / Work related Business				Social / Recreational				Shopping / Personal Business			
	MNL		Error Components		MNL		Error Components		MNL		Error Components	
Attributes	*Parameter*	*(t-ratio)*	*Parameter*	*(t-ratio)*	*Parameter*	*(t-ratio)*	*Parameter*	*(t-ratio)*	*Parameter*	*(t-ratio)*	*Parameter*	*(t-ratio)*
Constant (Current alt - Before)	-0.508	-2.200	-0.860	-2.380	-0.617	-2.710	-1.252	-2.300	-0.893	-3.800	-1.641	-3.300
Constant (Current alt - After)	-0.360	-1.460	-1.035	-2.170	-1.176	-4.170	-1.958	-3.430	-1.004	-3.670	-1.758	-3.060
Distance	0.006	6.670	0.006	9.580	0.005	6.060	0.006	9.310	0.009	6.800	0.011	9.770
Time of Day (Night)	0.730	0.570	-	-	3.631	3.610	4.264	2.860	3.735	1.980	5.285	2.670
Speeding	-4.125	-2.440	-2.631	-1.770	-2.285	-1.670	-3.136	-1.900	-4.798	-2.460	-4.449	-2.700
Travel time	-0.048	-1.210	-	-	-0.038	-1.020	-0.059	-1.860	-0.044	-1.190	-	-
Speeding x Travel time (interaction)	0.806	2.040	-	-	-0.178	-0.590	-	-	-0.193	-0.450	-	-
Charge	-0.001	-0.480	-	-	-0.010	-3.960	-0.012	-3.700	-0.028	-5.040	-0.034	-6.520
Error Components												
(Alternatives 1 & 2 - Before)			-1.373	-3.500			2.127	4.470			2.127	3.360
(Alternatives 1 & 2 - After)			1.935	2.930			1.934	3.520			2.019	3.560
Model Fit												
Sample	82		82		99		99		105		105	
Observations	328		328		396		396		420		420	
Log likelihood (0)	-360.189		-587.697		-427.261		-709.537		-438.069		-752.539	
Log likelihood (B)	-327.095		-313.855		-395.231		-367.642		-389.614		-368.452	
AIC	2.043		1.950		2.037		1.902		1.893		1.793	
McFadden Pseudo R-squared	0.092		0.466		0.075		0.482		0.111		0.510	

Table 6. WTP – Social / Recreational Trips

Social / Recreational	WTP	s.e.	(t-ratio)	Lower 95% CI	Upper 95% CI
Distance	$0.53	0.151	3.498	$0.23	$0.83
Time of day - Night	$3.54	1.662	2.127	$0.28	$6.79
Speeding	$2.60	1.535	1.694	-	-
Travel time	$4.87	3.226	1.511	-	-

Table7. WTP – Shopping / Personal Business

Shopping / Personal Business	WTP	s.e.	(t-ratio)	Lower 95% CI	Upper 95% CI
Distance	$0.32	0.059	5.471	$0.21	$0.44
Time of day - Night	$1.55	0.564	2.750	$0.45	$2.66
Speeding	$1.31	0.503	2.597	$0.32	$2.29

driving at night. Despite significant parameter estimates for speeding and travel time, the WTP ratios were not significant. The WTP for distance and night driving were also significant for shopping trips, although participants were not willing to pay as much as social trips for an additional kilometre or extra night driving. Surprisingly the WTP for speeding was significant for shopping trips. On average participants were willing to pay $1.68 to reduce their speeding behaviour. The fact that participants are willing to pay money to reduce this behaviour is somewhat counterintuitive given the nature of the charging regime (i.e., charges levied for speeding not vice versa). This highlights the negative perceptions of speeding held by the sample.

4 Conclusions

This paper details the development and application of a SC experiment designed to explore motorists sensitivities to a kilometre-based charging regime focused around crash-risk reduction. The contributions of the paper are as follows. First, it represents the first effort in Australia to focus specifically on charges based on risk-exposure as opposed to congestion-based charges or just kilometre-based charges. Second, it represents (to our knowledge) the first world-wide effort to apply jointly a SC experiment with a GPS experiment, where the GPS experiment is able to both provide the context for the SC, and is subsequently able to take advantage of the information obtained in the SC experiment to guide a simulation of the actual charging procedure (Bricka et al. 2009). We argue, this offers many advantages over transportation-based SC experiments which typically rely on asking participants what they did on a 'typical' trip and using that to form the reference alternative. People are notoriously bad at recollecting trip details, particularly over extended periods of time, which was the requirement for this study. In addition, people are very unreliable when it comes to the reporting of sensitive issues such as speeding (Greaves and Ellison 2010). Third, the paper demonstrates that values of crash-risk reduction and WTP vary quite markedly by the purpose of the trip. The findings suggest that for non-work trips people are sensitive to a risk based charging regime and are willing to change their driving behaviour in order to save money. In particular people are WTP substantial charges to maintain their driving behaviour, including overall distance (social/recreational and shopping/personal business trips), night driving (social/recreational trips only) and limiting driving time (social/recreational trips only). The WTP results for speeding reinforce the negative perceptions of speeding. The data collected in this study provides a unique opportunity to explore comparisons between what participants said they would do (SC) and what they actually did (RP). This important research is currently underway and future papers will address this issue directly.

Although not addressed in the current paper, the collected data is well placed to examine issues related to hypothetical bias. Given the data deals with driving behaviour, one would expect such biases to be present within the data as it is possible that respondents may have a different risk-taking profile when dealing with SC data than they would have in real life. Hypothetical bias has been deliberately ignored here however as the objective of the current paper is to examine the combining of GPS data with SC survey data. Future research will examine the issue of hypothetical bias. Further, despite dealing with speeding and night time driving, this paper does not seek to make conclusions regarding government policies related to issues surrounding road safety particularly in terms of road user’s willingness to pay to improve safety. A number of other research papers have addressed the specific issue of road safety through SC data (see e.g., Rizzi and Ortuzar 2003; Hensher et al. 2009). The focus of the paper is solely on the combination of GPS with SC data and the specific context was chosen as such data was capable of being captured by GPS. Thus, whilst policy implications are important, they are not the focus of this paper.

It is most likely that the reason GPS data has not been readily utilised in SC experiments (where applicable) is because collecting GPS data is a lengthy and costly process. Given the complex nature of this study, we believe that the benefits of integrating the data in this way largely outweighed any negatives. GPS devices are increasingly being used in many travel surveys to advance the accuracy of travel information (Stopher and Greaves 2009). With the improved affordability and consumer familiarity with GPS devices, the integration of GPS recorded travel information with SC experiments is a now a feasible solution which can help enrich the quality of SC experiments.

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