Forecasting the demand for an employee Park and Ride service using commuters' stated choices *

by

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Abstract

This paper uses Stated Choice (SC) data to forecast the demand for an employee Park and Ride service. Since it is well known that SC data contain sources of variation not present in Revealed Preference (RP) data we pay special attention to the scaling of the SC model. The results show that the modal shift away from parking-on site will be small unless the new service is accompanied by measures aimed at making parking on-site less attractive such as introducing parking charges.

Keywords: travel plan, stated choice, forecasting, scale factor

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1. Introduction

Encouraging employers to adopt travel plans is an important element of the UK Government's integrated transport strategy (DETR, 1998). The objective of a travel plan is to reduce the number of employees commuting alone by car to work and to encourage the use of more environmentally friendly modes such as public transport, cycling and walking. In recent years travel plans have become widely adopted in the UK, and have been proven to make a contribution to modal shift at the site level (Rye, 2002).

One of the measures that can be taken by the employer in order to reduce the number of commuters taking their car to the workplace is to introduce a Park and Ride service, i.e. a large off-site parking space with a shuttle-bus serving the workplace. This can be particularly effective in reducing car use if the workplace has poor public transport links and/ or limited parking space on-site. The University of St Andrews,[1] which is the subject of the current paper, qualifies in having relatively poor public transport links for a majority of employees and partly in having insufficient parking space relative to car users on-site, particularly for those employees working in the centre of town. It was therefore decided by the University that the possibility of introducing a Park and Ride service should be investigated further.

Since the Park and Ride service is yet to be implemented there does not exist any Revealed Preference (RP) data that can be used for model estimation. A feasible alternative approach is to carry out a Stated Choice (SC) experiment. Stated Preference methods (of which SC is a special case) have become increasingly popular in transportation research over the past two decades (see Hensher, 1994 or Ortuzar, 1999 for good introductions to the SP methodology). This is mainly due to the flexibility of the SP experiment to introduce new alternatives and attributes and to incorporate a wider range of attribute levels than what is observed in the market. It can also overcome problems often encountered with RP data such as little variance and/ or multicollinearity in the independent variables and measurement errors. The use of SP data has, however, also been met with much scepticism because of the hypothetical nature of the data. The question is simply how reliable data elicited from a hypothetical choice situation are. It is argued by several practitioners that SP data seems to be reliable given that the experiment is well designed and clearly explained to the respondents (e.g. Louviere *et al.*, 2000). There is also a growing body of evidence of successful use of SP models in forecasting (Beaton *et al.*, 1998; Fowkes and Tweddle, 1999).

This paper aims to forecast the share of car drivers that would switch to using Park and Ride given that such a service was provided. Section 2 describes the Stated Choice experiment, section 3 outlines the discrete choice methodology as well as the "scale problem" that needs to be taken into account when using SC models for forecasting. Section 4 describes the data and presents the modelling results and forecasts. Section 5 concludes.

2. The Stated Choice experiment

All members of University of St Andrews staff that on the day of the survey drove a car to work were asked to take part in the Stated Choice (SC) experiment. The commuters were asked whether they would choose to travel to work as usual or use Park and Ride if such a service was provided by the University. The SC experiment contained two attributes: Park and Ride door-to-door travel time and cost, which both varied over three levels relative to the individuals' current commute. The experiment was deliberately kept as simple as possible, i.e. with a low number of attributes and levels, since studies have shown that people give the most reliable answers when assessing changes in only two or three factors simultaneously (Bradley, 1988). More complex choice tasks may lead people to use so-called lexicographic choice rules, where only one attribute is considered at the time (Johnson and Meyer, 1984).

To increase the realism of the experiment the attributes of the Park and Ride option were based around the individuals' actual travel time and cost when going by car and parking on-site. As a consequence there will be some collinearity in the independent variables. It may be argued, however, that some degree of collinearity is acceptable if the realism of the experiment is enhanced. The full factorial design with two attributes varying over three levels provides 9 possible combinations of attribute levels ($3^2 = 9$). Nine choice scenarios were considered to be a manageable task for the respondents who were all presented with the full set of choices.

[Insert table 1 near here]

The respondents were given three options: 1) Choose park on-site, 2) Choose park and ride and 3) Don't know. The "Don't know" responses were left out when estimating the model.

3. Methodology

3.1 Derivation of a binomial logit model for mode choice.

The theoretical foundation of disaggregate travel demand models has its roots in Lancaster's (1966) microeconomic theory of consumer demand and the Random Utility Theory developed by Thurstone (1927), Marschak (1960) and McFadden (1973). In his theory, Lancaster postulated that the demand for goods depends on the characteristics or attributes of the goods rather than the goods *per se*. The basic structure of a random utility model is outlined below.

Let U_{ni} be the utility individual n derives from choosing transport mode i. It is assumed that the utility U_{ni} can be partitioned into a systematic component or "representative utility", V_{ni}, and a random component, e_{ni}. Assuming that the difference of the random terms, $e_n = e_{nj} - e_{ni}$, are distributed logistically and the number of alternatives, $J = 2$, we get the binomial logit model (see e.g. Ben-Akiva and Lerman, 1985) in which the probability that individual n chooses transport mode i is given by:

$$P_{ni} = \frac{1}{1 + e^{-\mu(V_{ni} - V_{nj})}} \qquad (1)$$

where μ is a positive scale parameter. The representative utility, V_{ni}, is a function of the attributes of mode i and the socio-demographic characteristics of individual n and is usually specified to be linear in parameters:

$$V_{ni} = \alpha_i' c_n + \beta' x_{ni} \tag{2}$$

where α_i and β are vectors of coefficients, x_{ni} is a vector of observed attributes relating to alternative i and individual n and c_n is a vector of observed characteristics of individual n.

The scale parameter, μ, can be shown to be inversely proportional to the error variance, σ_e^2 (see Ben-Akiva and Lerman, 1985):

$$\mu = \frac{\pi}{\sqrt{3\sigma_e^2}} \tag{3}$$

Since μ cannot be identified in estimation it is customary to impose the normalization $\mu = 1$, which is equivalent to assuming that the error variance equals $\frac{\pi^2}{3}$. The consequence of this normalisation is that the true scale parameter will be confounded with the α_i and β parameters. In other words we will be estimating $\mu\alpha_i$ and $\mu\beta$, not α_i and β. This causes some problems when using SC models for forecasting which we will discuss below.

3.2 Forecasting with SC models. The scale problem.

It is a well-known result that the binomial logit model will reproduce the market shares in the estimation sample such that:

$$\frac{1}{N}\sum_{n=1}^{N} y_{ni} = \frac{1}{N}\sum_{n=1}^{N} P_{ni} \tag{4}$$

where y_{ni} equals 1 if individual *n* is observed to choose alternative *i* and 0 otherwise. Because of this there are no serious implications of confounding the scale parameter with the coefficients in the representative utility function when using RP data for estimation, since the RP model nevertheless reproduces the market equilibrium embodied in the sample. SC data, however, do *not* in general embody information about the market equilibrium, and SC models will not reproduce the market equilibrium in simulation *unless* the error variance in the SC model equals the error variance in the RP model. This is easy to demonstrate if we recall that the scale parameter is inversely related to the error variance. Even if the true coefficients of the representative utility function are the same in the two models, $\alpha_i^{RP} = \alpha_i^{SC}$ and $\beta^{RP} = \beta^{SC}$, the forecasts from the two models will be different unless $\mu^{RP} = \mu^{SC}$ which will only be the case if $\sigma_{RP}^2 = \sigma_{SC}^2$.[2] Furthermore it can be shown that if $\sigma_{RP}^2 < \sigma_{SC}^2$ the SP model will overpredict the minor mode or the mode with the lower share (see appendix 1 for a numerical example).

This begs the question of whether or not the error variances from the RP and SC models are likely to be equal. The answer is unfortunately that they are not because the sources of the random terms in the two models will be different. The main sources of error in the RP model will be measurement error in the explanatory variables, taste differences (assuming β is equal for all *n* when in fact it is not), and model specification error such as wrong functional form and missing variables (see e.g. Train, 2003). While the latter two will clearly apply also in the SC model, measurement error is not likely to be a problem since the value of the attributes are given in the experiment. However, there is another important source of error in the SC model, namely that individuals might behave differently when making choices in an experimental setting compared to making choices in the market. McFadden (1986) points out that preferences may be unstable over the sequences of choices performed by the individual because of factors such as learning ("learning effects") and boredom ("fatigue effects"). Individuals might also be inclined to give biased responses on purpose in order to achieve some objective such as influencing the result of the study ("policy bias") or justifying their current behaviour ("justification bias") (Bates, 1988). As a consequence of the differences in the source of error in the different types of data Bates (1988) concludes that "it seems unlikely that a utility function as derived from SP analysis will be correctly scaled relative to the random effects which we hypothesise to be active in *real* choices". There is thus a need for rescaling the estimated coefficients in the SC model. We will discuss two of the most common methods below.

In general it is necessary to use additional RP data to rescale the SC coefficients. One straightforward way to do this is to rescale the coefficients to reproduce one or more coefficients from an RP model. This is the method which we will employ in the current paper. The second method is to estimate simultaneously the indirect utility function using SC *and* RP data by the method proposed by Morikawa (1989).[3] The coefficients of the indirect utility function are estimated along with the relative scale parameter, $\frac{\mu^{RP}}{\mu^{SC}}$. The joint estimation approach would be feasible in the present study if the SC experiment included users of other existing modes such as bus. Since we have chosen to focus on the switching behaviour of car drivers, however, we are unable follow this approach here.

4. Data characteristics and estimation results.

4.1 The sample data

Questionnaires were distributed to all members of St Andrews University Staff via the internal mail. Of the 1661 questionnaires that were distributed 642 were returned, giving a response rate of 38.7%. All car drivers were asked to complete the stated choice experiment. This yielded 255 responses with complete information about the work trip and socio-demographic characteristics that were used for model estimation. Prior to the main survey a pilot survey was carried out with members of the department of Economics, where several flaws in the original questionnaire were detected and subsequently corrected.

[Insert table 2 near here]

The individuals in the sample were categorized as academics or non-academics and divided into high and low income groups on the basis of their occupation. It is hypothesized that the low-income groups will be more willing to use the park and ride service as their opportunity cost of an increase in travel time may be lower. Furthermore, academics may be more aware of environmental issues than non-academics and hence more willing to switch to the "greener" mode.

It is possible that females are more dependent on the car than males since they are often responsible for tasks such as picking up children from school. The number of cars in a household may be a proxy for attitudes towards driving, in the sense that an individual living in a household with many cars may be less inclined to use other modes of transport compared to an individual who lives in a household with fewer cars.

A person who works in a building with limited parking space nearby is likely to be more willing to switch to Park and Ride than a person who works in a building with ample parking space. If he/ she arrives late to work this effect is expected to be stronger since finding a parking space will be even more difficult. It is expected that an individual who parks in a University car park is less likely to switch to Park and Ride, assuming that this is the individuals preferred parking option. Also, it is hypothesized that an increase in the travel time and cost of an alternative will lower the probability of this alternative being chosen. Finally, a marginal increase in walking time is likely to lead to a higher decrease in the probability compared to a marginal increase in the time spent travelling in the vehicle.

4.2 Estimation results

Table 3 below summarizes the estimation results of three different binary logit models (with t-statistics in parenthesis). The models were estimated using the method of maximum likelihood (McFadden, 1973).

[Insert table 3 near here]

In the simplest model (Model 1) only income, gender and the time and cost of the two alternatives enter as explanatory variables. The Park and Ride constant is positive and significant. This variable represents the mean impact of all variables that influence the choice of mode that are not included in the model. The coefficient for the female dummy is negative as expected but not significant on the 5% level. It is interesting to note that when the model was re-estimated omitting the respondents that chose the same mode in all scenarios the coefficient was significant in the opposite direction.[5] This indicates that when the females and males who find that going by car is the only option for them are omitted from the sample the remaining females are more likely to switch to Park and Ride than males.

Low-income academics are significantly more likely to switch to Park and Ride than individuals in the other income categories. There are no significant difference between high-income academics and non-academics (with high and low income). As expected the likelihood of switching to Park and Ride decreases significantly when the number of cars in the household increases. The coefficients for travel time and cost are also strongly significant in the expected direction.

In model 2 the variables that relates to the individuals' current parking situation are also included. As expected the individuals who work in buildings with relatively poor on-site parking are significantly more likely to use Park and Ride than those who have good parking facilities nearby. The ones who arrive late at work *and* work in a building with poor on-site parking are even more likely to switch to park and ride as hypothesized. The ones who arrive late and work in a building with good on-site parking are the least likely to switch. Individuals who currently park in University parking are found to be significantly more likely to switch to Park and Ride. The explanation for this somewhat surprising result may be that University parking is not necessarily the employees' preferred parking option. The signs and significance of the variables already included in model 1 do not change markedly apart from the Park and Ride constant which is no longer significant. The rho-bar squared increases from 0.127 in model 1 to 0.149 in model 2.

It is possible that the marginal disutility of an increase in travel time decreases as travel times increase. This can be accommodated by entering the time variable in square-root form in the representative utility function.[6] In this case the marginal utility of a change in travel time is given by:

$$MU_T = \frac{\partial V}{\partial T} = \frac{\beta_T}{2\sqrt{T}} \tag{5}$$

where β_T is the coefficient for the square-root of travel time for a given mode and T is the travel time for that mode for a given individual (suppressing the individual subscript for simplicity). Model 3 re-estimates model 2 after taking the square root of travel time. This leads to a small increase in rho-bar squared from 0.149 to 0.151.

It is also possible that people find travelling by car less onerous than travelling by shuttle bus. Using the Park and Ride will also entail some waiting time, which is usually regarded as more onerous than travelling in the vehicle. We have taken this into account in Model 4 by estimating a separate time coefficient for car and Park and Ride. As expected the car mode has a lower coefficient than that of Park and Ride. It is likely that the people who currently have to park relatively far away from their workplace will be more likely to switch to Park and Ride. This is also accommodated in Model 4 by separating the travel time into walking time (from parking to workplace) and in-vehicle travel time (and waiting time for Park and Ride).[7] The coefficient for walking time is significant in the expected direction.[8] Note that even though the magnitude of the coefficient is lower than the coefficient for in-vehicle time the marginal disutility of an increase in walking time can still be higher than that of an increase in in-vehicle time since walking times are in general much lower (see equation 5). The rho-bar squared increases markedly from 0.151 in Model 3 to 0.167 in Model 4.

We also tested for learning and fatigue effects using the scaling method outlined in Bradly and Daly (1994). The theoretical foundation of the scaling method is given in section 3. Testing for fatigue/ learning effects involves estimating separate scale parameters for each choice task in the experiment. One of the scale parameters needs to be normalized to unity for identification purposes (typically the first or the last in the choice sequence). If the scale parameters are found to increase in the number of choice tasks performed this is evidence of a learning effect since in this case the individuals behave more consistently when making their last choices (recall that when the scale increases the error variance falls). If the opposite is true there is evidence of fatigue effects, i.e. people behaving less consistently in the last choices performed. The null hypothesis of equal scale parameters in Model 4 cannot be rejected at the 5% significance level using the LR test (see appendix 2 for the estimation results).[9] There is also no substantial difference in the coefficient estimates of the two models. This supports previous findings in the literature (Bradly and Daly, 1994; Sœlensminde, 2001), which conclude that strong fatigue effects are unlikely when offering no more than 10 choice comparisons within a single experiment.

4.3 Forecasting results

For the reasons discussed in section 3 it may be necessary to rescale the estimated coefficients in the SC model before proceeding to forecast the modal split. An alternative forecasting method proposed by Fowkes and Preston (1991) is to average the probabilistic and the deterministic forecasts. The deterministic forecast is given by assuming that the mode with the higher representative utility is the chosen mode for all individuals in the sample. The random component of the model is thus ignored. The logic behind the Fowkes and Preston method is that the probabilistic forecast is likely to overpredict the minor mode while the deterministic forecast is likely to overpredict the major mode (Fowkes and Preston, 1991) (this holds when the error variance of the SC model is higher than that of the RP model). The correct forecast is therefore likely to be bounded by these forecasts. This hypothesis is supported empirically by Beaton *et al.* (1998). In the following we will compare the forecasts derived from the Fowkes and Preston method with the forecasts using the method of rescaling using a known RP coefficient.

As mentioned in section 3 the method of rescaling requires an RP estimate of one or more of the coefficients in the representative utility function. In an RP discrete choice model of commuters' mode choice in St Andrews the cost coefficient was estimated to be –0.14 (see Hole, 2003 for a detailed description of the data and estimation results). It can be seen from table 3 that it would be necessary to rescale the SP coefficients by a factor of 1.4 to reproduce the RP cost coefficient. As a consequence the forecasts derived from the SC model without rescaling is likely to overpredict the share of Park and Ride users since rescaling by a factor higher than one implies that the error variance in the SC model is higher than that of the RP model (see section 3).

In order to produce the forecasts of the share of car drivers switching to Park and Ride it was necessary to estimate the Park & Ride travel time for all individuals in the sample. The estimates depend on which area of town the individual works and his/ her travel route into town. Needless to say the precision of the forecasts will depend on the accuracy of the estimated Park and Ride travel times.

The forecasts derived from the procedures outlined above assuming that the cost of going by car and Park and Ride are the same are summarized in table 4 below.

[Insert table 4 near here]

It can be seen from the table that the SC model without rescaling predicts that 18.5% of the car drivers will switch to Park and Ride using the probabilistic method while the deterministic forecast is that 0.4% will switch. The mean of these forecasts give the Fowkes and Preston prediction (9.5%). The forecast derived from the rescaled model, perhaps the most reliable of the four, predicts that 12.1% of the car drivers will switch to Park and Ride.

Apart from the probabilistic forecast from the model without rescaling (which is likely to be an overestimate) neither of the forecasts imply that a large percentage of car drivers will switch to Park and Ride. One of the measures that could be taken in order to encourage a larger take-up of the service is introducing on-site parking charges. In order for this strategy to be effective the charges would have to be coordinated with the local (Fife) Council so that car drivers do not merely switch from parking on-site to parking in the street.[10] The forecasts below are calculated assuming that the cost of parking on-site has increased by £1 following the introduction of parking charges.

[Insert table 5 near here]

As expected all forecasting methods suggest that the introduction of parking charges will increase the switching to Park and Ride. The SC model without rescaling now predicts that 36.6% of the car drivers will switch using the probabilistic method and that 13.9% will switch using the deterministic method. The forecast derived from the rescaled model predicts that 32.7% of the car drivers will switch to Park and Ride, which is somewhat higher than the Fowkes and Preston forecast (25.3%).

5. Conclusions

It can be seen from the previous analysis that the share of car drivers switching to Park and Ride will be relatively low unless supported by measures designed to make parking on-site less attractive such as introducing parking charges. This supports previous findings in the literature on travel plans (Rye, 2002) as well as the advice given in the UK government's travel plan guide (DETR, 1999) that a travel plan is most effective in reducing car use when it contains a combination of "sticks" and "carrots". In other words an effective travel plan should include measures aimed at discouraging car use as well as measures aimed at encouraging more environmentally friendly modes.

Parking charges seem to be justified as a means to deter driving as the current situation of providing free parking at the worksite actually subsidizes car use (Porter, 1999). Indeed Shoup (1997) finds that on average the cost of parking equals 75% of the variable cost of commuting by car. In this light the introduction of a parking charge is simply making the drivers pay a higher share of the variable cost of driving themselves.

An employee Park and Ride service seems to have the potential to be effective in reducing the demand for on-site parking when supported by measures to deter parking on-site. It is likely to be particularly effective at workplaces located in small towns (such as St Andrews) with poor public transport links and relatively limited parking facilities, although it could be considered at any workplace with little on-site parking or where the aim is to reduce the availability of on-site parking.

References

Bates, J. (1988) "Econometric Issues in SP Analysis". *Journal of Transport Economics and Policy* 22(1), pp. 59-69.

Beaton, P., Chen, C. and Meghdir, H. (1998) "Stated Choice: A Study in Predictive Ability Using an Aggregate Truth Set". *Transportation* 25(1), pp. 55-75.

Ben-Akiva, M.E. and Lerman, S. (1985) *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge.

Bradley, M. and Daly, A. (1994) "Use of the Logit Scaling Approach to Test for Rank-Order and Fatigue Effects in Stated Preference Data". *Transportation* 21(2), pp. 167-184.

Bradley, M. (1988) "Realism and Adaptation in Designing Hypothetical Travel Choice Concepts". *Journal of Transport Economics and Policy* 22(1), pp. 121-137.

DETR, (1998) *A New Deal for Transport: Better for Everyone*. DETR, London.

DETR, (1999) *A Travel Plan Resource Pack for Employers*. DETR, London.

Fowkes, A.S. and Tweddle, G. (1999) "Validation of Stated Preference Forecasting: A Case Study Involving Anglo-Continental Freight". In J.D. Ortuzar (ed.), *Stated Preference Modelling Techniques*, PTRC Education and Research Services Limited, London.

Fowkes, A.S. and Preston, J. (1991) "Novel Approaches to Forecasting the Demand for New Local Rail Services". *Transportation Research A* 25(4), pp. 209-218.

Hensher, D.A. (1994) "Stated Preference Analysis of Travel Choices: The State of the Practice". *Transportation* 21(2), pp. 107-133.

Hole, A.R. (2003) *Modelling commuters' mode choice in Scotland*. Ph.D. Thesis, Department of Economics, University of St Andrews.

Johnson, E. J. and Meyer, R.J. (1984) "Compensatory Choice Models of Noncompensatory Processes: The Effect of Varying the Context". *Journal of Consumer Research* 11(1), pp. 528-541.

Lancaster, K.J. (1966) "A New Approach to Consumer Theory". *Journal of Political Economy* 74(2), pp. 132-157.

Louviere, J.J., Hensher, D.A. and Swait, J.D. (2000) *Stated Choice Methods: Analysis and Application*. Cambridge University Press, Cambridge.

Marschak, J. (1960) "Binary Choice Constraints on Random Utility Indicators," K. Arrow (ed.). *Stanford Symposium on Mathematical Methods in the Social Sciences*, Stanford University Press, Stanford.

McFadden, D.L. (1986) "The Choice Theory Approach to Market Research". *Marketing Science* 5(4), pp. 275-297.

McFadden, D.L. (1973) "Conditional Logit Analysis of Qualitative Choice Behaviour". In P. Zarambeka (ed.), *Frontiers in Econometrics*, 105-142, Academic Press, New York.

Morikawa, T. (1989) *Incorporating Stated Preference Data in Travel Demand Analysis*. Ph.D. Thesis, Department of Civil Engineering, MIT.

Ortuzar, J.D. (1999) "Fundamentals of Stated Preference". In J.D. Ortuzar (ed.), *Stated Preference Modelling Techniques*, PTRC Education and Research Services Limited, London.

Porter, R.C. (1999) *Economics at the Wheel. The Costs of Cars and Drivers.* Academic Press, San Diego.

Rye, T. (2002) “Travel Plans: Do They Work”. *Transport Policy* 9(4), pp. 287-298.

Sælensminde, K. (2001) “Inconsistent Choices in Stated Choice Data. Use of the Logit Scaling Approach to Handle Resulting Variance Increases”. *Transportation* 28(3), pp. 269-296.

Shoup, D. (1997) “The High Cost of Free Parking”. *Journal of Planning Education and Research* 17(1), pp. 3-20.

Thurstone, L. (1927) “A Law of Comparative Judgement”. *Psychological Review* 34(2), pp. 273-286.

Train, K.E. (2003) *Discrete Choice Models with Simulation*. Cambridge University Press, Cambridge.

Wardman, M. (1988) “Comparison of RP and SP Models of Travel Behaviour”. *Journal of Transport Economics and Policy* 22(1), 71-91.

Appendix 1. Numerical example of a forecast derived from a wrongly scaled SC model.

Let us assume that the representative utility of mode 1 and 2 are given by:

$$V_{n1} = -0.2 \times TIME_{n1} - 0.1 \times COST_{n1}$$

$$V_{n2} = -0.2 \times TIME_{n2} - 0.1 \times COST_{n2}$$

The travel times and cost of the two modes for a hypothetical individual are given in the table below. It is easy to see that in this case the SC model will over-predict the demand for the minor mode by 78% given that the SC scale is half the size of the RP scale ($\mu^{SC} / \mu^{RP} = 0.5$).

Table A1. Travel time and cost of two alternatives.

Alternative	Time	Cost
1	5	10
2	15	5

Table A2. Comparison of the forecasts derived from the RP and SC models assuming the SC scale is half the size of the RP scale.

V^{RP}	V^{SC}	P^{RP}	P^{SC}
-2	-1	0.82	0.68
-3.5	-1.75	0.18	0.32

Appendix 2. Estimation results for Model 4 allowing for different scale parameters.

Variable	Model 4	Model 4*
Constant for Park and Ride	1.267 (3.27)	1.399 (2.45)
Female	-0.188 (-1.54)	-0.288 (-2.01)
Academic – High income	0.206 (1.33)	0.176 (1.04)
Academic – Low income	0.596 (3.38)	0.719 (3.50)
Non-Academic – High income	-0.075 (-0.47)	-0.144 (-0.75)
Number of cars in household	-0.091 (-2.36)	-0.230 (-2.190)
Limited on-site parking	0.515 (3.86)	0.528 (3.13)
Arrive at work later than 9am	-0.558 (-1.93)	-0.704 (-2.10)
Interaction	0.709 (2.07)	0.863 (2.17)
Park in University parking	0.692 (4.44)	0.760 (3.96)
Cost	-0.010 (-7.27)	-0.011 (-4.66)
Square-root of time (car)	-1.931 (-14.79)	-1.964 (-7.62)
Square-root of time (P&R)	-2.317 (-15.34)	-2.362 (-7.67)
Square root of walking time	-0.837 (-7.91)	-0.848 (-5.58)
Scale parameters:		
(t-statistics w.r.t. 1)		
Choice 1 (base)		1.000
Choice 2		1.064 (0.39)
Choice 3		0.691 (-1.55)
Choice 4		1.013 (0.08)
Choice 5		1.219 (1.07)
Choice 6		0.743 (-1.02)
Choice 7		0.955 (-0.24)
Choice 8		0.983 (-0.07)
Choice 9		0.678 (-1.49)
Log-likelihood	-1013.12	-1009.52

Table 1: The full SC design. The attributes are those of Park and Ride relative to the individual's current commute.

Question	Park & Ride	
	Cost (in pence)	Time (in minutes)
1	0	+5
2	0	+10
3	0	+15
4	-50	+5
5	-50	+10
6	-50	+15
7	-100	+5
8	-100	+10
9	-100	+15

Table 2. Description of variables and data characteristics.

Dummy Variables	Sample Share
Academic – High income	24%
Academic – Low income	14%
Non-Academic – High income	22%
Non-Academic – Low income	40%
Female	54%
Currently park in university parking	82%
Arrive at work later than 9am	15%
Work in a building with limited on-site parking	55%
Continous Variables	**Mean value**
Door-to-door commuting time in minutes	20.5
Walking time in minutes	2.7
Travel cost in pence (calculated as 15 pence pr mile)	163
Number of cars owned by household	1.7

Table 3. Estimation results for the Binary Logit Models.

Variable	Model 1	Model 2	Model 3	Model 4
Constant for Park and Ride	0.761 (3.41)	-0.157 (-0.59)	-0.052 (-0.19)	1.267 (3.27)
Female	-0.193 (-1.68)	-0.231 (-1.91)	-0.216 (-1.79)	-0.188 (-1.54)
Academic – High income	0.136 (0.93)	0.203 (1.34)	0.161 (1.07)	0.206 (1.33)
Academic – Low income	0.335 (2.08)	0.631 (3.63)	0.548 (3.14)	0.596 (3.38)
Non-Academic – High income	-0.032 (-0.211)	-0.036 (-0.23)	-0.189 (-1.22)	-0.075 (-0.47)
Number of cars in household	-0.187 (-2.60)	-0.144 (-1.94)	-0.187 (-2.42)	-0.091 (-2.36)
Limited on-site parking		0.658 (5.29)	0.558 (4.51)	0.515 (3.86)
Arrive at work later than 9am		-0.555 (-1.94)	-0.567 (-1.97)	-0.558 (-1.93)
Interaction (late*limited parking)		0.557 (1.65)	0.645 (1.90)	0.709 (2.07)
Park in University parking		0.626 (4.12)	0.703 (4.63)	0.692 (4.44)
Cost	-0.010 (-7.17)	-0.010 (-7.24)	-0.010 (-7.21)	-0.010 (-7.27)
Time	-0.208 (-14.65)	-0.215 (-14.81)		
Square-root of time			-2.054 (-14.41)	
Square-root of time (car)				-1.931 (-14.79)
Square-root of time (P&R)				-2.317 (-15.34)
Square root of walking time				-0.837 (-7.91)
Number of respondents in sample	255	255	255	255
Number of responses	2105	2105	2105	2105
Log-likelihood:				
Constant only L(c)	-1224.414	-1224.414	-1224.414	-1224.41
Final value L(β)	-1065.078	-1036.455	-1033.989	-1013.12
Rho-squared (with L(c))	0.130	0.154	0.156	0.173
Rho-squared adjusted (with L(c))[4]	0.127	0.149	0.151	0.167

Table 4. Predictions of the modal shares derived from the different forecasting approaches assuming that travel costs are the same for the two modes.

Mode	Probabilistic- No scaling	Deterministic	Probabilistic – Rescaled	Fowkes & Preston
Car	81.5%	99.6%	87.9%	90.5%
Park & Ride	18.5%	0.4%	12.1%	9.5%

Table 5. Predictions of the modal shares derived from the different forecasting approaches assuming that the cost of parking on-site is £1 higher than using Park and Ride.

Mode	Probabilistic- No scaling	Deterministic	Probabilistic – Rescaled	Fowkes & Preston
Car	63.4%	86.1%	67.3%	74.7%
Park & Ride	36.6%	13.9%	32.7%	25.3%

Endnotes

1 St Andrews is a small town of about 18000 inhabitants located in the rural North-Eastern part of Fife, Scotland. The town's main employer is the University followed by the tourism industry.

2 Note that it is also possible, of course, that $\alpha_i^{RP} \neq \alpha_i^{SC}$ and $\beta^{RP} \neq \beta^{SP}$. Wardman (1988) examines the equality of coefficients of several SC and RP models and concludes that there is evidence of equality given that heterogeneities in the sample are accounted for.

3 See also Bradley and Daley (1994) for a similar joint RP/SC estimation procedure which can be carried out using standard econometric software.

4 The rho-squared adjusted statistic is given by $1-\left[\dfrac{N \times LL(\beta)}{(N-k)\times LL(c)}\right]$, where N is the sample size and k is the number of coefficients in the model.

5 This model is not reported here.

6 It is also possible to use the natural logarithm of the variable but this resulted in a model with a markedly lower rho-square.

7 This is possible assuming that Park and Ride walking times will be close to zero.

8 We also tried interacting the travel time components and cost but the interaction effects were all found to be insignificant

9 The LR statistic is given by $2\times\left[LL^{U}-LL^{R}\right]=2\times\left[-1009.52-(-1013.12)\right]=7.19$, where LL^{U} and LL^{R} are the log-likelihoods of the model with free and restricted scale parameters respectively.

10 The majority of parking in St Andrews has charges that are higher than the ones suggested here. There are, however, a small number of free parking spaces around town.