Commuting in small towns in rural areas: the case of St Andrews[*]

by

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Abstract

Since many rural commuters depend on the private car due to lack of convenient public transport, car reduction policies designed for large cities with ample public transport may be unsuitable for smaller towns. In particular, pricing policies designed to encourage public transport use may be less effective, as commuters with no convenient substitute to driving will be unable to switch. This paper develops multinomial and mixed logit models of commuters' mode choice using data from a survey of commuters in the University of St Andrews. We find that the direct elasticities of the car mode are comparable to estimates reported in studies of commuting in larger urban areas, while the demand for public transport is considerably more elastic. The value of in-vehicle time is found to be about half of the UK average, reflecting that the roads in the St Andrews area are relatively uncongested.

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1. Introduction

There have been many studies of commuting in urban areas in the UK, but relatively little research has been done on commuting in small towns in rural areas. Rural commuting differs from urban commuting in several important respects: there is little or no road congestion, a parking space is usually provided free by the employer and the supply of convenient public transport is often limited (Nutley, 1998). As a result a high share of rural commuters will depend on the private car to get to their workplace. Another consequence of these differences is that car reduction policies designed for large cities with ample public transport may be unsuitable for smaller towns. In particular pricing policies (such as congestion charges) may be less effective in reducing the share of drivers and encouraging public transport use in rural areas, as commuters with no convenient substitute to driving are unable to change mode. Since pricing policies will only be effective once a substitute is in place, improving public transport service quality is likely to be the most important policy tool to reduce driving in rural areas. It follows that in order to design effective policies to encourage use of public transport, policies must be based on evidence from studies focusing explicitly on rural commuters as one cannot *a priori* expect important policy parameters such as elasticities to be equal across geographical locations where commuting conditions differ markedly (Acutt and Dodgson, 1995).

St Andrews is a small town of about 18000 inhabitants[1] located in the rural North-Eastern part of Fife, Scotland. It is a typical Scottish small town in that it has rather limited public transport links, but somewhat untypical in being the location of Scotland's oldest University. The main mode of commuting is the private car

[1] Including students.

followed by walking and cycling. Public transport has a relatively low market share, although some people commute by bus. Train is hardly used at all for commuting, as the nearest train station (Leuchars station) is about 5 miles away from the town with a relatively poor bus connection.

The current paper develops multinomial logit and mixed logit models of work-trip mode choice estimated using data from a survey of employees of the University of St Andrews, the town's main employer. The models are subsequently used to estimate aggregate direct and cross mode-choice elasticities and the value of travel time savings. The outline of the paper is as follows: section 2 gives an outline of the mixed logit model, section 3 describes the data as well as providing some descriptive results from the survey, section 4 presents the modelling results and section 5 offers some policy recommendations and concluding remarks.

2. The mixed logit model [2]

We assume a sample of N commuters with the choice of J transport modes. The utility that individual n derives from choosing mode i is denoted by U_{ni}. We assume without loss of generality that utility can be partitioned into two systematic components and two random components such that:

$$U_{ni} = \left[\alpha_i' c_n + \beta' x_{ni}\right] + \left[\eta_{ni} + \varepsilon_{ni}\right] \qquad (1)$$

where α_i and β are vectors of coefficients, x_{ni} is a vector of observed attributes relating to mode i and individual n and c_n is a vector of observed characteristics of person n. η_{ni} is a random term whose distribution over alternatives and people

[2] This section draws on Brownstone and Train (1999).

depends on underlying parameters and observed data relating to alternative i and individual n and ε_{ni} is a random term which is assumed to be IID extreme value. Since η_{ni} may be correlated over alternatives the mixed logit model does not suffer from the restrictive Independence from Irrelevant Alternatives property (Luce, 1960). When η_{ni} is zero for all individuals/ alternatives, the mixed logit model reduces to the multinomial logit model.

We denote the density for η_{ni} as $f(\eta_{ni}|\theta)$ where θ are the fixed parameters of the distribution. The probability of person n choosing alternative i *conditional* on knowing η_{ni} is given by:

$$L_{ni}(\eta_{ni}) = \frac{e^{\beta' x_{ni} + \eta_i}}{\sum_j e^{\beta' x_{nj} + \eta_j}} \tag{2}$$

which is the standard logit formula. However, the researcher does not know η_{ni}, and the *unconditional* probability of person n choosing alternative i is given by integrating the logit formula over all values of η_{ni}:

$$P_{ni}(\theta) = \int L_{ni}(\eta_{ni}) f(\eta_{ni}|\theta) d\eta_{ni} \tag{3}$$

The mixed logit probability is thus a weighted average of the logit formula evaluated at different values of η_{ni}, with the weights given by density f. This expression cannot be solved analytically, and is therefore approximated using simulation methods (see e.g. Brownstone and Train, 1999 and Train, 2003).

3 Data and descriptive statistics

3.1 Data characterization

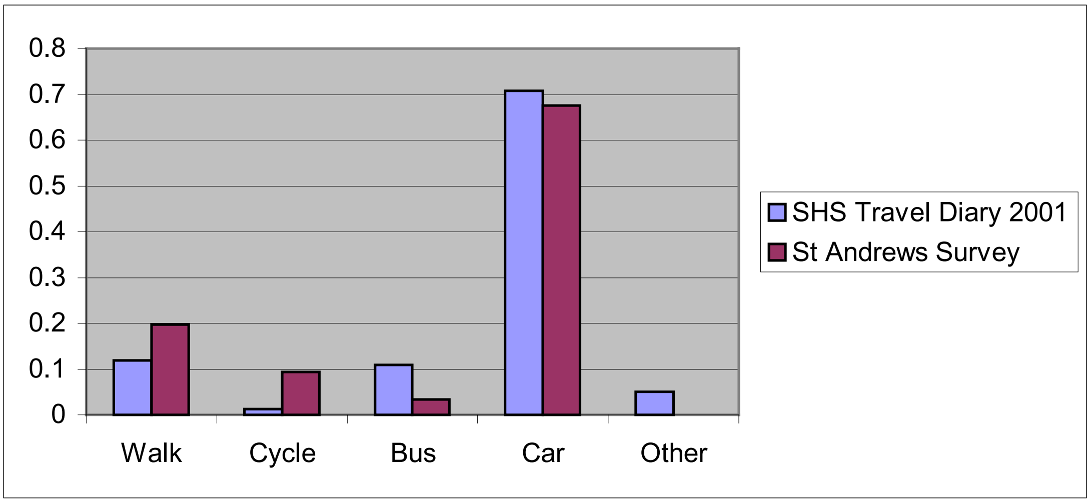
As part of the development of a travel plan for the University of St Andrews a survey of employees' commuting behaviour was undertaken with questionnaires distributed to all members of St Andrews University staff. The survey collected information on the current mode used for commuting, socio-demographic variables such as occupation and car ownership as well as public transport availability at home and near the workplace. Of the 1661 questionnaires that were distributed 642 were returned, giving a response rate of 38.7%. 585 responses with complete information about the work trip and socio-demographic characteristics were used for model estimation. A list of the variables with some descriptive statistics is given in table 1 below.

It can be seen from the table that the majority of commuters travel by car to work followed by walking and cycling, while only a small share of the commuters travel by bus. The relatively high shares of commuters who walk and cycle relative to the national average (see figure 1) reflects that a large proportion of the University staff live in the St Andrews area and that walking and cycling conditions are relatively favourable. The low share of commuters who travel by public transport is a result of the fairly poor bus service in the area. It can be seen from table 1 that 62% of the commuters in the sample do not have access to an hourly bus service going to and from their home to their workplace and that bus fares are relatively high with an average fare of £1.96 for a one-way ticket.

Table 1 Description of variables and data characteristics.

Mode	Sample Share
Walk	19.7%
Cycle	9.4%
Bus	3.4%
Car	67.5%
Choice set	
Walk available	25%
Cycle available	52%
Bus available	88%
Car available	91%
Alternative attributes	Mean/ Share
Door-to-door commuting time in minutes	
Walk	13.5
Cycle	12.1
Bus	36.8
Car	18.1
Walking time in minutes	
Walk	13.5
Cycle	1.2
Bus	14.0
Car	2.8
Travel cost in pence	
Bus	195.8
Car	122.7
Frequency of bus service to and from work	
Less than 2 buses per hour	88%
Less than 1 bus per hour	62%
Socio-economic variables	Mean/ Share
High income	44%
Number of cars in household	1.4

Figure 1 Comparison to the modal split for commuting trips in the 2001 Scottish Household Survey Travel Diary.



It is well documented in the literature that there are differences between men and women's commuting behaviour, in particular in terms of bicycle use. In a recent study, Dickinson *et al.* (2003) find that females are significantly less likely than males to cycle to work and equally car dependent in spite of having shorter commutes. The explanation may be that women have more complex trip characteristics than men due to tasks such as transporting children and shopping and/ or are more concerned with safety issues. In our models gender enters as a dummy explanatory variable (1= female, 0= male), which allows us to examine whether there is a similar difference between male and female commuting behaviour in the St Andrews area.

It is expected that the more cars a household owns, the more likely the individuals living in the household are to travel by car to work. Car ownership may be considered endogenous to the mode-choice decision as argued by Train (1980), who suggests a joint car-ownership/ mode-choice model using a nested logit structure. Given that our data set contains few variables that are relevant to the households' car ownership decision we are unable to follow this approach in the present paper. Since our models estimate mode choice conditional on car ownership, they represent a short-run response to a change in the policy variables.

In addition to the socio-economic characteristics of the commuters, it is expected that the attributes of the modes are important determinants of mode choice. In particular the travel time and cost of the modes have been found to be significant explanatory variables in virtually all studies of commuting behaviour. In addition, it is expected that the more frequent the bus service, the more likely the individual is to travel by public transport.[3] The frequency of the bus service is represented as two dummy variables, indicating whether the individual has access to an hourly/ less frequent bus service (with a frequency of more than one bus per hour being the reference category). The respondents self-reported the in-vehicle/ cycling time and walking times for their chosen mode. The travel time components for the alternative modes were calculated by regressing travel time on distance for each mode, using the estimated regression equations to calculate travel times for the non-chosen modes for all individuals in the sample.[4] It is hypothesized that an increase in the travel time of an alternative will lower the probability of the alternative being chosen. Furthermore, a marginal increase in walking and cycling times is expected to lead to a higher decrease in the probability compared to a marginal increase in the time spent travelling in a motor vehicle.

[3] In a previous survey of staff commuting in the University of St Andrews (University of St Andrews, 2002) improving key elements of service quality such as the frequency and reliability of buses was found to be most important both to current public transport users and other commuters when asked what would encourage them to use public transport more often.

[4] We estimated separate OLS regression equations for bus and car in-vehicle time, cycling time and walking time. Walking time for the bus mode is calculated as the estimated walking time to the nearest bus stop, while walking times for the cycle and car modes are calculated as the average walking time for these modes.

It is expected that an increase in the cost of a mode will decrease the probability of the mode being chosen. The respondents self-reported the pecuniary cost of travelling by bus to work, while the cost of going by car was calculated as 15 pence per mile.[5] Car costs include variable costs such as petrol and servicing costs but not fixed costs such as road tax and insurance, and also neglecting depreciation.[6] Walking and cycling is assumed to be costless.

3.2 Choice set formation

When estimating a discrete choice model the available alternatives for each individual must be pre-determined by the researcher. For each individual in the sample the available choice set is considered to be walk, cycle, bus and car with some exceptions. Going by car is considered unavailable to individuals without a driver's licence and to those living in a household without a car. Going by bus is considered unavailable to individuals who reported to have no bus service available, as well as to those living too close to work for bus to be a practical alternative.[7] Walking to work is considered feasible for individuals commuting one mile or less, while going by bicycle is considered feasible for all respondents commuting three miles or less.[8]

It can be seen from table 2 that the majority of individuals who currently walk and cycle to work live within a one and three mile radius of the University respectively. It is also interesting to note that the majority of the respondents who live

[5] In order to calculate the cost of the bus mode for those respondents who did not report it themselves we regressed the bus fare on distance, using the estimated regression equation to calculate the fare.
[6] The variable cost was calculated using a fuel price of 79p per litre, assuming a fuel consumption of 36 miles per gallon. The average costs of tyres, servicing and repairs per mile is calculated using figures given by the Automobile Association.
[7] Bus is not considered to be a practical alternative if the combined distance to and from bus stops exceeds the distance from the commuter's home to her workplace.
[8] The British Medical Association (1992) suggests that 3 miles is within cycling distance for most people. Although there are some individuals in the sample walking more than one mile and cycling more than three miles to work, these assumptions seem reasonable to us.

within a one mile radius of their workplace walk to work (72%) while only about 16% of the individuals who live within a three mile radius cycle. This finding implies that there is considerable scope for increasing the share of individuals cycling to work.

Table 2 Cross-tabulation of commuting distance and mode choice

	Dist <=1 miles	Dist <=3 miles	Dist >3 miles
Walk	72%	45%	0%
Cycle	11%	16%	4.5%
Bus	0%	2%	4.5%
Car	17%	37%	91%
Total	116	254	331

4. Estimation results

The estimation results for the multinomial logit models are summarized in table 3 below. In all the models gender, car ownership and the time and cost of the alternatives enter as explanatory variables. In the model presented in columns 3 and 4 (Model 1) the attributes of the alternatives (door-to-door travel time and cost) are entered in levels, implying that the marginal utility of a change in an alternative attribute is constant. The coefficient for the walk constant is positive and significant at the 5% level, while the coefficients for the cycle and bus constants are positive and negative respectively and insignificant. The alternative specific constants represent the mean impact of all variables that are not included in the model that influence the choice of a mode.

Table 3 Multinomial logit mode choice models

Variable	Alternative	Model 1 (MNL)		Model 2 (MNL)	
		Coeff.	t-stat.	Coeff.	t-stat.
Constant	Walk	2.359	5.62	4.405	5.47
Constant	Cycle	0.308	0.72	2.162	2.01
Constant	Bus	-0.220	-0.38	1.463	2.46
Female	Cycle	-1.720	-4.54	-2.150	-5.06
Bus frequency – 1 or more per hour (ref)					
Bus frequency – less than 1 per hour	Bus	-1.913	-2.52	-1.482	-1.90
Number of cars in household	Car	0.603	2.55	0.533	1.94
Travel time (door-to-door)	All	-0.048	-2.90		
Log of walking time	All			-1.794	-7.89
Log of cycling time	Cycle			-1.837	-4.39
Log of in-vehicle time	Bus, Car			-0.615	-1.90
Cost	All	-0.010	-2.44	-0.012	-2.81
Observations		585		585	
Log-likelihood: constant only L(c)		-241.543		-241.543	
Log-likelihood: final value L(β)		-212.462		-167.532	
Rho-squared (with L(c))		0.120		0.306	
Rho-squared adjusted (with L(c))		0.113		0.299	

The coefficient for car ownership is positive and significant as expected, indicating that the utility of going by car increases significantly in the number of cars the household owns. The coefficient for gender is negative and significant for the bus mode, which implies that females have a significantly higher disutility of going by bicycle to work. This confirms the finding in Dickinson *et al.* (2003). It should be noted that when interacting the occupation and gender variables, female academics were found to be as likely to cycle as male non-academics (they were, however, less likely to cycle than male academics).[9] Female non-academics are the least likely to cycle. No significant differences between the genders were found in terms of walking and public transport use.

[9] This model is not reported here.

As expected an increase in the bus frequency leads to an increase in the probability of choosing bus. Although the difference between having an hourly service or a more frequent service was not found to be significant, there is a significant difference between having and not having an hourly service. This implies that the provision of an hourly bus service is an important incentive in order to encourage more commuters to travel by public transport. The coefficients for (door-to-door) travel time and cost are negative and significant on the 5% and 10% level respectively.

The commuters' income[10] was not found to be a significant determinant of mode choice and is therefore not included in the final model specifications reported in table 3. Some of the influence of income on mode choice will nevertheless be incorporated through the car ownership variable, as income is found to have a strong influence on households' car ownership level (Train, 1980; Hensher *et al.*, 1989; Pendyala *et al.*, 1995).

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 natural logarithm of travel time in the representative utility function. In this case the marginal utility of a change in travel time is given by:

$$MU_T = \frac{\partial V}{\partial T} = \frac{\beta_T}{T} \tag{4}$$

where β_T is the coefficient for the log of travel time for a given mode and T is the travel time for that mode for a given individual (suppressing the individual subscript

[10] The individuals in the sample were divided into high and low income groups on the basis of their occupational rank in the University.

for simplicity). In the model presented in columns 5 and 6 (Model 2), travel time enters in the log form.[11] Furthermore, door-to-door travel time is subdivided into in-vehicle/ cycling time and walking time. All the travel time components have the expected sign and are significant on the 5% level, except the coefficient for in-vehicle time, which is significant on the 10% level. It can be seen that this specification leads to a considerable increase in the rho-bar squared compared to Model 1.

A crucial question that faces the analyst when applying the mixed logit model is which parameters that should be allowed to vary as well as which distribution to use for the random parameters. As in Hensher (2001b), Carlsson (2003) and Alpizar and Carlsson (2003) we specify the cost variable to be fixed, while the time parameters are specified to follow a normal distribution.[12] Fixing the cost coefficient is convenient for several reasons: it ensures that the value of time has finite moments (Brownstone, 2000) and that the sign of the cost variable is negative for all respondents.[13] The standard deviations of the coefficients for the walking and in-vehicle time variables were found to be insignificant, however, and constraining the standard deviations of those coefficients to equal zero did not lead to decrease in the rho-bar squared. The estimation results of the more parsimonious model with fixed walking and in-vehicle time coefficients and normally distributed cycling time coefficient are reported in table 4 below.[14] This model structure implies that the error variance of the cycle mode is higher than that of the other alternatives. The alternatives remain uncorrelated,

[11] We also tried entering the cost variable in the log form, but this specification resulted in a model with a lower rho-square.
[12] We also attempted to specify the time coefficients to follow a triangular distribution as in Hensher (2001a), but this resulted in a model with a lower rho-bar squared.
[13] When the time coefficient is random and the cost coefficient fixed the distribution of the value of time is distributed in the same way as the time coefficient (Revelt and Train, 1999; Carlsson, 2003).
[14] The model is estimated using Kenneth Train's GAUSS code with 500 Halton draws.

however, since the cycling time variable only enters the utility function of the cycle mode.[15]

Table 4 Mixed logit mode choice model

Variable	Alternative		Model 3 (ML) Coeff.	t-stat.
Constant	Walk	Mean	5.797	5.90
Constant	Cycle	Mean	3.543	2.57
Constant	Bus	Mean	2.323	3.01
Female	Cycle	Mean	-2.979	-4.36
Bus frequency – 1 or more per hour (ref)				
Bus frequency – less than 1 per hour	Bus	Mean	-1.301	-1.48
Number of cars in household			0.717	2.11
Log of walking time	All	Mean	-2.550	-6.12
Log of cycling time	Cycle	Mean	-3.150	-4.16
		Std. Dev.	1.161	3.88
Log of in-vehicle time	Bus, Car	Mean	-0.966	-2.04
Cost	All	Mean	-0.013	-2.04
Observations			585	
Log-likelihood: constant only L(c)			-241.543	
Log-likelihood: final value L(β)			-162.05	
Rho-squared (with L(c))			0.329	
Rho-squared adjusted (with L(c))			0.321	

It can be seen that the sign and significance of the coefficients in Model 3 are similar to those in Models 1-2. All the time coefficients are significant on the 5% level and have the expected sign along with the coefficients on cost, gender and car ownership. The coefficient on bus frequency, however, has the expected sign but is insignificant. This is likely to be a result of the relatively low number of individuals in the sample choosing bus, which makes it harder to obtain precise estimates of the bus-specific coefficients.

[15] We tried adding error components to the utility specification to induce correlation between the alternatives but none of the error components were found to be significant. As a result we decided on the more parsimonious Model 3 as our preferred model.

4.1 Elasticities

Aggregate elasticities provide a summary measure of the likely response to a change in an alternative attribute and are therefore valuable tools that can assist in developing efficient car-reduction policies. The aggregate elasticities derived using Model 3 are reported in table 5 below. The elasticities are calculated by simulating the change in the modal shares following a 1% increase in a given alternative attribute using the method of sample enumeration (Ben-Akiva and Lerman, 1985). Since the models do not allow for traffic generation, these elasticities should be interpreted as mode-choice elasticities.

It can be seen from table 5 that the demand for bus is quite elastic, with a bus fare elasticity of -1.156. Indeed this is higher than what is found in most studies of urban commuting. Dargay and Hanly (2002), find that the short-run bus fare elasticity for England as a whole is around –0.4 and that elasticities at the county level vary widely (between 0 and –1.6), although the authors suggest that the county specific elasticities should be interpreted with caution due to the low number of observations. In a comprehensive review, Dargay and Hanly (1999) find that the average short-run bus fare elasticity is -0.3.[16] The high elasticity estimate in the present study is likely to be related to the fact that bus fares in the St Andrews area have doubled over the last decade, as there is evidence that the demand for public transport is more price sensitive at higher fare levels (Dargay and Hanly, 2002). Since the elasticity measures the percentage change in the modal share from the base share, however, the increase in the share of bus users is not as substantial as the elasticity estimate might imply. Nevertheless, the estimate suggests that subsidising bus fares would be an important

[16] It should be noted that the elasticity estimates reported in Dargay and Hanley are regular elasticities as they also take traffic generation into account. Oum *et al.* (1992) argue that mode-choice elasticities may serve as lower bounds for regular elasticities in terms of absolute values.

factor to incentivise more commuters to use public transport. The walking time elasticity for the bus mode is also higher than what is found in most studies, indicating that decreasing walking times by increasing the number of bus stops will substantially increase the share of commuters travelling by bus. The bus in-vehicle time elasticity is markedly lower than the walking time elasticity, which implies that commuters are less sensitive to changes in the time spent travelling by bus than to changes in access and egress times.

Table 5 Aggregate elasticities

	Percentage change in the probability of choosing			
Due to a 1% change in	Walk	Cycle	Bus	Car
Cycling time	0.140	-0.802	0.151	0.064
In-vehicle time (Bus)	0.001	0.016	-0.441	0.019
In-vehicle time (Car)	0.060	0.175	0.385	-0.060
Walking time (Walk)	-0.320	0.326	0.013	0.046
Walking time (Cycle)	0.140	-0.721	0.114	0.054
Walking time (Bus)	0.002	0.043	-1.160	0.049
Walking time (Car)	0.158	0.465	1.044	-0.160
Bus costs	0.001	0.022	-1.156	0.052
Car costs	0.013	0.105	0.875	-0.060

The direct car cost elasticity is found be –0.06, which is comparable in size but somewhat lower than the car cost elasticity reported in most studies of urban commuting (Oum *et al.*, 1992, provide a review of car cost elasticities derived form discrete choice models). This confirms our prior expectation that increasing the cost of driving is not likely to be an effective deterrent to car use unless a convenient alternative mode of transport is provided. The walking time and in-vehicle time elasticities for the car mode are also found to be relatively low, indicating that an increase in travel time will not lead to a substantial decrease in car use. Bus is found to be the closest substitute to car, as the cross elasticities with respect to a change in a car attribute is higher for bus than for the other modes. Given that walking and cycling are only considered available for relatively short commutes this result is expected. The direct walking and cycling time elasticities are found to be -0.320 and -0.802 for the walk and cycle modes respectively. Given that the time spent walking and cycling is closely related to commuting distance, these elasticity estimates reflect how the probability of walking and cycling to work changes as a result of increasing/ decreasing the distance from the home to the workplace.

4.2 The value of travel time savings

Prior to undertaking investments in transport infrastructure it is important to assess the benefits of the investment. It is generally held in the literature that a significant proportion of the benefits of infrastructure improvements is due to road users' travel time savings. In a recent study, Mackie *et al.* (2001) suggest that the value of travel time savings (*VTTS*) accounts for 80% of the monetised benefits within the cost benefit analysis of major road schemes in the UK. It follows that in order to make well-informed investment decisions it is crucial to obtain as precise estimates of *VTTS* as possible, and in many countries the authorities have commissioned studies estimating *VTTS* both for commuting and other types of trips (the UK, the Netherlands and the Scandinavian countries among others). Since the multinomial and mixed logit models are rooted in microeconomic theory, the value of travel time savings can be shown to be given by the ratio of the travel time and cost coefficients when the alternative attributes enter in levels in the model (see for instance Truong and Hensher, 1985). When travel time enters in the logarithm form (as in models 2 – 3), *VTTS* is a decreasing function of travel time:

$$VTTS = \frac{\beta_T}{\beta_C}\frac{1}{T} \tag{5}$$

where β_T and β_C are the time and cost coefficients for a given mode and *T* is the travel time for that mode. The estimated values of travel time savings evaluated at the average time for each travel time component, using models 2 – 3, are given in table 6 below.

Table 6 Values of time (in pence per minute)

	Walking time	Cycling time	In-vehicle time (Bus, Car)
MNL	20.28	13.99	2.69
ML – Mean	26.61	22.14	3.90
ML – Std. Dev.		8.16	

It can be seen that the commuters are on average willing to pay more for a decrease in the time spent walking compared to a decrease in cycling time, which indicates that walking is considered more onerous than cycling. Furthermore, a marginal decrease in cycling time is valued higher than a marginal decrease in in-vehicle time, indicating that cycling is considered more onerous than travelling in a motor vehicle. The significant standard deviation of the cycling time coefficient in the mixed logit model implies that some commuters have a comparatively low value of cycling time, while others have comparatively high values of cycling time (29% of the commuters in the sample find cycling more onerous than walking).[17] It is interesting to note that the value of time estimates derived from the ML model are substantially higher than those derived from the MNL model, which is consistent with the finding in Hensher (2001a). This is an important result, as it implies that user benefits of previous road projects may be underestimated.

In a review of British studies reporting the value of in-vehicle travel time savings, Wardman (1998) finds an average value of 5.64 pence per minute, which is considerably higher than the average value of in-vehicle time found in the present study.[18] It is likely that the low *VTTS* estimate reflects the fact that roads in the St Andrews area are relatively uncongested. Calfee and Winston (1998) and Hensher (2001a) find, using data from the USA and New Zealand respectively, that the value of time spent travelling under congested conditions is substantially higher than time spent travelling in free-flow traffic.[19] Since the UK average value of in-vehicle time is calculated using data from urban as well as rural areas and therefore partially reflects substantially more congested commuting conditions than those in the St Andrews area, the national average *VTTS* should be expected to be higher than that in the present study.

The average value of walking time is found to be about 7-8 times higher than the estimated value of in-vehicle time, and about 4-5 times higher than the UK average in-vehicle *VTTS*. This is comparable to the findings of studies of commuting in urban areas. The average value of cycling time is about 5-6 times higher than the estimated value of in-vehicle time and about 2-4 times higher than the national

[17] 0.33% of the commuters in the sample are found to have a positive cycling time coefficient. It is not unlikely that for some cycling enthusiasts the time spent cycling is a good rather than a bad.
[18] Given that most of the studies in the review are likely to have used the MNL model to derive the estimate of *VTTS*, the most representative estimate for comparison with the review is perhaps that derived from the MNL model.
[19] In Calfee and Winston (1998) the value of congested travel time is found to be 3 times higher than that of uncongested/ free-flow travel time. A similar result is obtained by Hensher (2001).

average in-vehicle *VTTS*. We know of no other studies reporting the value of cycling time for commuting trips in the UK. Given the relatively favourable cycling conditions in St Andrews, the value of cycling time found in the present study is likely to be lower than that in urban areas where cycling by many is perceived to be dangerous due to heavy traffic, particularly in the absence of segregated cycle lanes which are more common in continental cities.[20] As there are few studies reporting the value of cycling time to date, more research is needed to investigate how the value of cycling time varies between geographical locations and according to the facilities provided.

5. Concluding remarks

This paper has developed multinomial and mixed logit mode choice models using data on commuters in the University of St Andrews. As St Andrews is located in a rural area with limited public transport supply it was expected that key policy variables such as elasticities and values of time would differ from those reported in studies of commuting in larger urban areas. We found that the direct elasticities of the car mode were comparable to the estimates of studies reported in studies of urban commuting, while the demand for public transport was found to be considerably more elastic. Although this is partially a result of the fact that bus has a substantially lower market share in St Andrews compared to larger towns and cities, the finding nevertheless indicates that there is scope for increased use of public transport for commuting in St Andrews and other small towns in rural locations. The values of in-

[20] Noland and Kunreuther (1995) and Ortúzar et. al. (2000) investigate how changes in travel conditions influence individuals' choice of travelling by bicycle.

vehicle travel time were found to be lower than in most studies of urban commuting, reflecting that the roads in the St Andrews area are relatively uncongested. The value of walking time is found to be about 7-8 times higher than the value of in-vehicle time, while the value of cycling time is, on average, about 60% - 80% of the value of walking time. More research is needed to investigate how the value of cycling time varies across geographical locations and according to the facilities provided.

References

Acutt, M.Z. and J.S. Dodgson (1995) "Cross Elasticities of Demand for Travel", Transport Policy 2(4), pp. 271-277.

Alpizar, F. and F. Carlsson (2003) "Policy Implications and Analysis of the Determinants of Travel Mode Choice: An Application of Choice Experiments to Metropolitan Costa Rica", Environment and Development Economics 8(4), pp. 603-619.

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

British Medical Association (1992) *Cycling: Towards Health and Safety*, Oxford University Press, Oxford.

Brownstone, D. (2000) "Discrete Choice Modelling for Transportation", Resource Paper, 9th International Association of Travel Behaviour Conference, Gold Coast, Australia, 1-7 July.

Brownstone, D. and K.E. Train (1999) "Forecasting New Product Penetration with Flexible Substitution Patterns", Journal of Econometrics 89, pp. 109-129.

Calfee, J. and C. Winston (1998) "The Value of Automobile Travel Time: Implications for Congestion Policy", Journal of Public Economics 69, pp. 83 -102.

Carlsson, F. (2003) "The Demand for Intercity Public Transport: The Case of Business Passengers", Applied Economics 35(1), pp. 41-50.

Dargay, J.M. and M. Hanly (2002) "The Demand for Local Bus services in England", Journal of Transport Economics and Policy 36(1), pp. 73-91.

Dargay, J.M. and M. Hanly (1999) "Bus Fare Elasticities: Report to the Department of the Environment, Transport and the Regions", ESRC TSU, December.

Hensher, D., P. Barnard, N. Smith and F. Milthorpe (1989) "An Empirical Model of Household Automobile Holdings", Applied Economics 21(1), pp. 35-57.

Hensher, D. (2001a) "The Valuation of Commuter Travel Time Savings for Car Drivers: Evaluating Alternative Model Specifications", Transportation 28, pp. 101-118.

Hensher, D. (2001b) "Measurement of the Valuation of Travel Time Savings", Journal of Transport Economics and Policy 35(1), pp. 71-98.

Nutley, S. (1998) "Rural areas: The accessibility problem", in B. Hoyle and R. Knowles (eds.), *Modern Transport Geography*, pp. 185-215, Wiley, Chichester.

Luce, D. (1960) *Individual Choice Behaviour*, John Wiley and Sons, New York.

Mackie, P.J., S. Jara-Diaz and A.S. Fowkes (2001) "The Value of Travel Time Savings in Evaluation", Transportation Research E 37, pp. 91-106.

Noland, R. B. and H. Kunreuther (1995) "Short-Run and Long-Run Policies for Increasing Bicycle Transportation for Daily Commuter Trips", Transport Policy 2(1), pp. 67-79.

Oum, T.H., W.G. Waters II and J.S. Yong (1992) "Concepts of Price Elasticities of Transport Demand and Recent Empirical Estimates", Journal of Transport Economics and Policy 26(2), pp. 139-154.

Ortúzar, J. de D., A. Iacobelli, C. Valeze (2000) "Estimating demand for a cycle-way network", Transportation Research Part A 34, pp. 353-373.

Pendyala, R.M., L.P. Kostyniuk and K.G. Goulias (1995) "A Repeated Cross Sectional Evaluation of Car-Ownership", Transportation 22(2), pp. 165-184.

Revelt D. and K.E. Train (1998) “Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level”, Review of Economics and Statistics 80(4), pp. 647-657.

Train K.E. (1980) “A Structured Logit Model of Auto Ownership and Mode Choice”, Review of Economic Studies 47(2), pp. 357-370.

Truong P. and D. Hensher (1985) “Measurement of Travel Time Values and Opportunity Cost from a Discrete-Choice model”, The Economic Journal 95, pp. 438-451.

University of St Andrews (2002) *Travel Plan*, assisted by Colin Buchanan and Partners.

Wardman, M. (1998) “The Value of Travel Time: A Review of British Evidence”, Journal of Transport Economics and Policy 32(3), pp. 285-316.