Incorporating habits into an agent based model of commuting mode choice

Helen Bowkett, Kiron Chatterjee, Graham Parkhurst (Centre for Transport & Society, University of the West of England, Bristol)

Abstract

Following a behavioural economics approach, which brings insights from psychology into standard economic models, the utility maximising model for the choice of journey mode is extended to include habitual behaviour. The model applies Triandis' Theory of Interpersonal Behaviour (1977) to commuters' mode choice decision with five choices: car, bus, rail, and cycle and the option not to travel. Following Triandis, the mode choice decision is determined by either the commuters intended mode, based on utility maximisation, or the mode they habitually used. Both are affected by facilitating conditions, such as the availability of a public transport service and the possession of a driving licence.

This paper focusses on an application of the model to demonstrate the evolution of bus patronage with and without the inclusion of habit as a behavioural influence in the context of a car-restraint policy based on periodic increases in parking charges and a policy of providing free bus travel for the elderly. The model is implemented using an agent based modelling approach; the advantages of which are further demonstrated through a refinement deploying latent class analysis to enable multiple-segmentation of the agent population. It is concluded that ABM techniques for mode-choice decisions are more resource extensive to establish, but these costs can be reduced by integration with existing analysis tools and are strongly justified by the additional functionality provided. This makes the ABM approach particularly relevant for assessing sustainable mobility policies, as the changes often relate to small groups of individuals, subtle personal characteristics and interpersonal interactions are often significant, and behavioural responses often show important time-lags following intervention.

1. Introduction

The growth in car use in urban areas is resulting in adverse environmental impacts and leading to longer and more unreliable journey times. In response, policy makers in many areas are considering interventions that will encourage people to switch to public transport, walking or cycling. At the larger scale such interventions include the provision of new rapid transit systems and the introduction of road user charging. More local, smaller scale initiatives, often targeted at specific areas or groups, are also considered. The quality of the business cases for such measures depends on the accuracy of the forecasts of the number of users of these schemes, yet the numbers involved are often small, which brings a challenge to the preparation of these forecasts. In addition, some measures, such as the provision of a new bus route serving an area of employment or a new housing development, require forecasts of passenger numbers as they evolve over time, in order to evaluate the total amount of subsidy required for such a service.

This paper presents a mode choice model based on behavioural economics, which seeks to increase the 'explanatory power of economics by providing it with more realistic psychological foundations', (Camerer 2003). A typical behavioural economics model takes a standard neo-classical approach but modifies one or two assumptions based on psychological insights with the aim of producing a model which gives better predictions, as it is based on more realistic assumptions. This study focuses on the mode used by commuters, as many sustainable transport policies are aimed at producing a switch away from regular car trips made during peak hours.

The psychological understanding underlying the model developed for this study is that commuting is often a habitual choice, rather than a deliberate choice on every occasion, as assumed in the current models based on standard 'rational actor' neo-classical economic assumptions. Habits are automatically repeated behaviours, with little or no conscious consideration giving to alterative actions even if those were demonstrably more effective (Verplanken et al. 1997). They result in 'strong associations between goals (e.g. going to work) and actions (e.g. using a car)' (Aarts and Dijksterhuis, 2000). The use of the car for such a trip becomes automatic and no deliberation over the choice of mode occurs; rather the behaviour becomes script-driven (Garling *et al.*, 2001). The enactment of habitual choices may be interrupted by external shocks, for example by temporary road closures or the withdrawal of parking spaces (Gardner 2009, Brown *et al.* 2003, Fujii *et al.,* 2001) or by changes in the internal context of people's lives, such as following a change in residential or work location (Clark *et al.,* 2014, Bamberg, 2006). The next section outlines the theory related to habitual behaviour.

2. Habit and Triandis' Theory of Interpersonal Behaviour

Social psychologists have observed that behaviour tends to be unchanged for long periods and, in order to conceptualise understanding of these phenomena, have developed habit theory which hypothesises that behaviour, when first initiated, is the product of rational decision making, but when repeated in a stable context becomes automatic or scripted, even if circumstances change. The 'habit-discontinuity hypothesis' posits that habits may become weakened when routine behaviours, such as commuting, are interrupted by a contextual change (Verplanken et al., 2008).

The role of habits in behavioural choices was recognised by Triandis in his Theory of Interpersonal Behaviour (1977) presented in Figure 1 below.

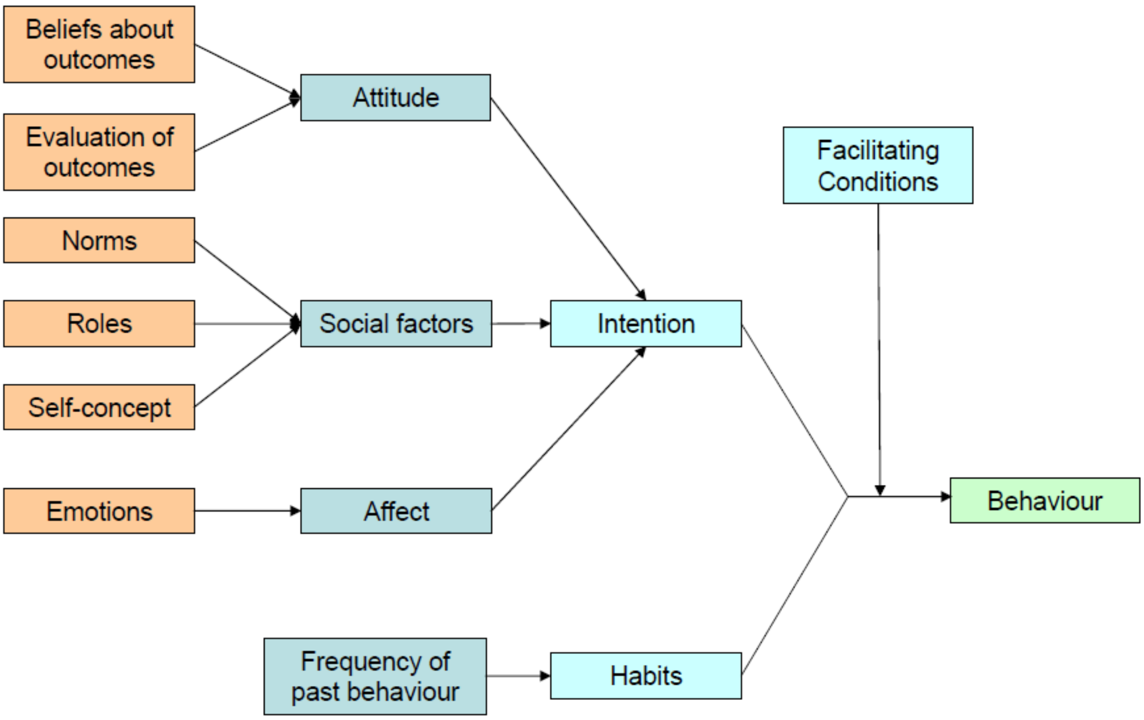

Figure 1: Triandis' Theory of Interpersonal Behaviour (1977) Source: Jackson, 2005

In this theory, a person's **intended** behaviour is determined by attitude, social factors, and affect. Attitude refers to the extent to which the individual has a positive or negative evaluation of performing the behaviour under consideration. This depends upon three factors: first, beliefs about the outcome, for example, the desirability of the outcome, second, evaluation of the outcome, for example, how likely is it to succeed, and third, whether the benefits exceed the costs of undertaking the behaviour and any associated risks (Chatterton, 2011). Social factors include norms, roles and a person's self-concept. Social norms are the usually-expected behaviours in society and relate to how people behave in general in society. Roles are defined by Triandis as 'sets of behaviours that are considered appropriate for persons holding particular positions in a group' and relates to how other people holding a similar position in society behave. Self-concept is a person's perceived identity, such as, for example, if they identify with pro-environmental climate change believers and wish to avoid the use of fossil fuels in their travel arrangements. Emotions (affect) describe a person's mood at the time of the behavioural decision, which combined with the attitude and social factors, result in a person's intended behaviour.

In the context of the current paper, however, a key point is that the actual behaviour exhibited may be different from a person's behaviour as predicted by intention alone, as a result of the influence of **habits**. Triandis considered there to be a trade-off between intention and habits, and that strong habitual behaviour can overwhelm intended behaviour. It is the role of habits in this theory which is applied in the current paper to add greater psychological realism to the mode choice modelling of commuter travel.

The actual behaviour undertaken can also be affected by facilitating conditions. These are personal or external factors which may help or hinder a person from carrying out their intended or habitual behaviour. Triandis' description of facilitating conditions covers a person's 'ability to perform the act', 'the difficulty of the act', and 'possession of the knowledge required to perform the act and environmental factors that increase the probability of the act'.

Behavioural economics places an emphasis on empirical data as a source of guidance as to which assumptions in a standard neo-classical economics model can usefully be relaxed in an attempt to provide a more realistic foundation to an economic model. For this study, the model form and methodology was informed by a survey conducted for the UK Department of Transport (DfT) as part of its research into transport and climate change. The remainder of this paper is structured as follows: Section 3 describes the data set; the model is described in Section 4 and model results are presented in Section 5; a discussion of the practicalities of extending the model to the geographical area of a particular policy maker's interest is the topic of Section 6 and opportunities for further work are discussed in the final section.

3. Description of the data set

The data used in this study was collected for the DfT from 3,923 face-to-face, in-home interviews conducted between November 2009 and June 2010 with adults (aged 16 plus) living in England as part of a study into Climate Change and Transport Choices. Respondents completed a detailed questionnaire on their travel behaviour and attitudes, with 626 of these people also completing a stated preference (SP) exercise between four modes of travel (car, bus, rail and cycle) for a 5-mile regular commuting trip.

The evidence for the role of habits came from the answers to the question given to everyone that reported using a car at least once or twice a week. Although regular use of a car does not necessarily mean that it is habitual, the responses for people in employment showed that, for many, using the car is something they do 'frequently' (85%), 'automatically' (73%) and 'belongs to their routine' (85%).

The survey also asked about personal constraints on mode choice, covering aspects such as having mobility issues or other disabilities which prevent the use of a particular mode, being required to have a car available for use during the working day or needing to be able to carry work equipment and papers. Six percent of respondents had a disability or other health issue which meant that they could not use buses, 9% had difficulties going out on foot and 16% of respondents had a long-standing health issue that made cycling difficult or impossible. The largest single personal constraint was the lack of a car licence (17%).

The evidence for triggers which cause people to re-consider their commuting mode was provided when people who had made regular journeys to work in the last six months and had changed the way they usually travelled to work were asked what factors had prompted that change. Of the 157 respondents to this question, 22% reported that their change of mode was a result of changing their job or place of work and 16% said it was a result of moving house. These two types of event may have made other people reconsider their commute to work, even if they then continued to use the same mode as previously (and so would not have been expected to respond to the question). Twenty-four percent of respondents said that they had changed mode because the new mode was quicker or more convenient and 16% because the new mode was cheaper or free. These findings were therefore consistent with those from other studies that have identified the main influential life events on travel mode choice for adults to be moving house, changing work location, acquiring a car and becoming a parent (Chatterjee *et al.,* 2013, Prillwitz *et al.,* 2006; Klockner, 2004; Van der Waerden *et al.*, 2003).

The stated preference exercise asked respondents to choose between car, bus, rail, cycle or not travelling for a 5-mile journey to work. The journey for each mode was described in terms of:

- Cost: 150, 200, 250 or 300 pence
- Time: 15, 30, 45 60 or 75 minutes
- Carbon emissions: 1, 2, 3 or 4 kg

This part of the survey enabled the estimation of each respondent's personal preferences for particular modes and the weightings they placed on time, cost and carbon emissions when considering their choices between alternative modes.

4. Model Description

The aim of the model was to incorporate habitual behaviour into a model of mode choice. An agent based modelling (ABM) methodology was selected as this 'bottom up' approach is well suited to modelling individuals and for creating a dynamic model which traces their choices over time and records the resulting passenger numbers for each part of the transport system. ABM software is designed to handle data about individual agents. It can easily record the previous choices made by each person and use this information when modelling an agent's choices in subsequent time periods. This makes it well suited for implementing a mode choice model that incorporates habitual behaviour.

The core components of an agent based model (ABM) are:

- the agents
- the environment
- the interactions between agents, and between each agent and the environment.

A typical ABM is an artificial world of heterogeneous, autonomous agents, each following a set of rules governing their behaviour in an attempt to achieve their own goals. (O'Sullivan and Haklay, 2000). The environment is 'everything that surrounds the agents, but which is distinct from the agent and its behaviour' (Teahan, 2010). The emphasis in the ABM approach is to establish a few simple behavioural rules in the model and then observe the emerging behaviour of the system as individuals follow these rules over time.

In the model of commuter mode choice developed for this study there are 626 agents; each agent is one of the respondents in the DfT SP survey. The model is run for 520 time periods, representing each week for ten years. Each agent is making the same 5-mile journey to work. There are four available modes: car, bus, train, cycle or the agent can choose not to travel. In the first modelled period each agent chooses the mode that gives them the highest utility. In subsequent time periods they use the same mode as before (habitual behaviour) unless a trigger event occurs, in which case they make an intentional mode choice using the standard neo-classical maximum utility rule. The utilities are calculated based on each agent's personal preference for time, cost, carbon dioxide emissions and mode constant as calculated from an analysis of the responses in the SP survey.

The triggers for re-considering the mode used by a respondent for their daily commute are moving house or changing job. The probability of a person moving house, by gender and age, in each model time period, was estimated from the British Household Panel Survey. The probability of someone changing job in each model time period, again by gender and age, was estimated from OECD job tenure data.

Facilitating conditions were represented in the model by personal constraints which exclude certain modes from an individual's choice set, e.g. if health issues prevent cycling or there is lack of an available bus service.

The agents in the model have the personal characteristics and constraints of the 626 respondents in the SP survey. They age as the model progresses over time and when agents reach age 68 they are replaced with an agent that inherits their characteristics but joins the model at age 16. The model was implemented in Python. This is a widely known computer language and is used as the scripting language in several major transport modelling software packages.

5. Model Results

The impact of habitual behaviour

The model was first run as a standard utility maximisation model without any habitual behaviour. The model is set to reflect transport market conditions which apply to Wales. Bus fares are set to rise at 4% each year, as bus fares rose in Wales in real terms by 3.9% in 2013 and 4.9% in 2014 (DfT Transport Statistics Table BUS0415). Car costs are set to decline in real terms over time at the rate set out in the DfT's WebTAG Unit A1.3 (DfT, 2014), as the predicted increases in fuel efficiency in car engines outweigh the real increases in fuel cost. Train fares are assumed to rise at 1% per annum reflecting the current regulatory regime for rail fares. In all cases the time of travel by each mode was kept constant, but travel times as well as costs could be changed in model runs if desired. All the input values in a model run are set in a csv file which is read into the model at the start of each run together with another csv file that contains the details of each agent in the model.

The total number of people using each mode, when there is a steady change in costs over time for each mode and commuters choose the mode that gives them the highest utility in each time period, is shown in Figure 2 below. It shows a general increase in car use and decline in bus use over time as the relative cost of motoring declines.

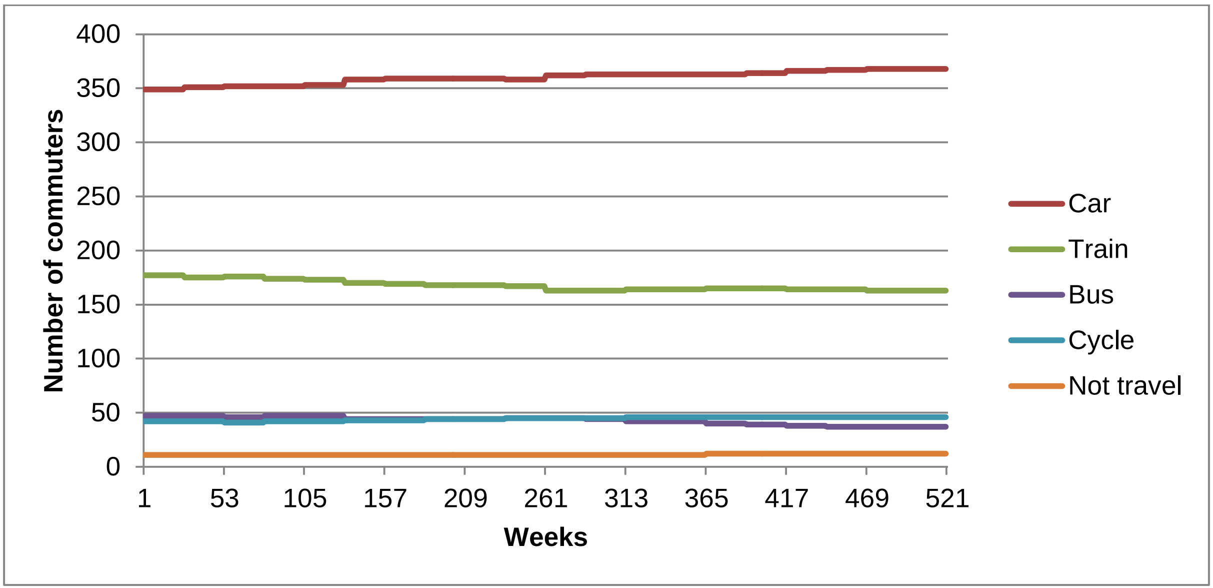

Figure 2: Number of commuters by mode

The focus of analysis for the present paper is the number of bus users in each modelled scenario. When habitual behaviour is included there is variability in the number of bus users between runs due to the stochastic nature of the timing of trigger events. Each scenario was run 100 times and the average results are shown in the subsequent figures. Figure 3 compares the number of bus users with and without the incorporation of habitual behaviour. The introduction of habitual behaviour results in a higher number of bus passengers than would otherwise be the case, as some people continue to travel by bus even though, over time, it has become more expensive relative to other modes.

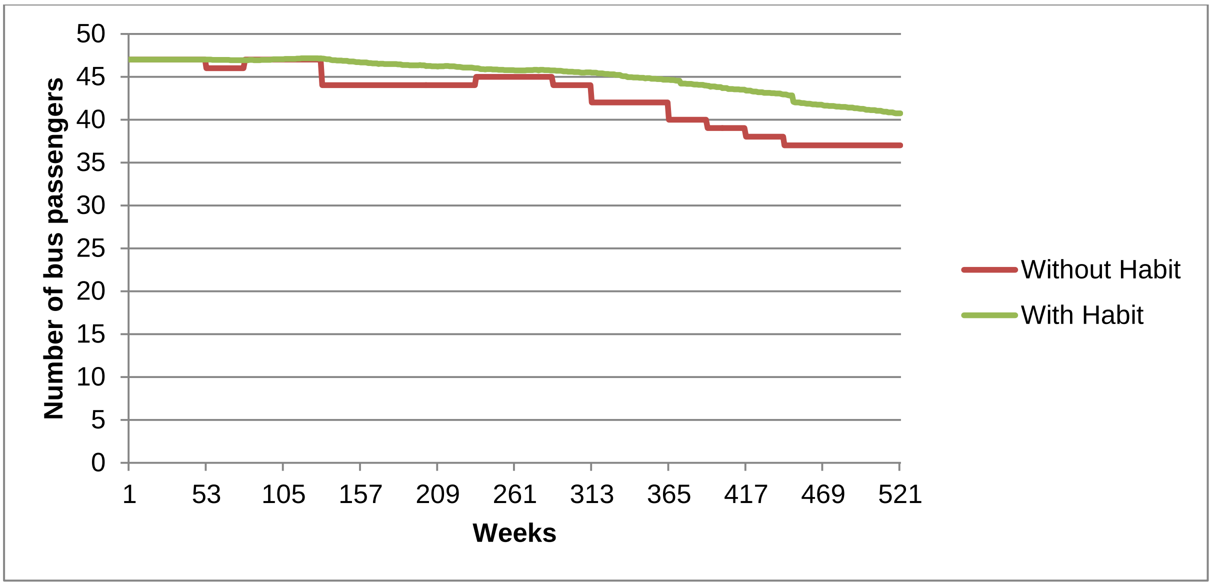

Figure 3: Number of bus commuters, with and without modelling of habitual behaviour

The difference between the two forecasts becomes more noticeable when the model is also used to test a parking policy designed to deter car use which involves increases in parking charges and in the number of cars liable to pay the charge at the beginning of years 3, 6 and 8. This represents a policy to extend the area covered by a controlled parking zone in the main employment area. The forecast of bus users in this scenario is shown in Figure 4 below and shows clearly that habitual behaviour leads to a lag in response to changes to costs in the transport system. In this case the number of bus passengers is lower with the incorporation of habitual behaviour as car drivers do not respond immediately to the rise in car costs and the subsequent switch of some car drivers to bus is delayed.

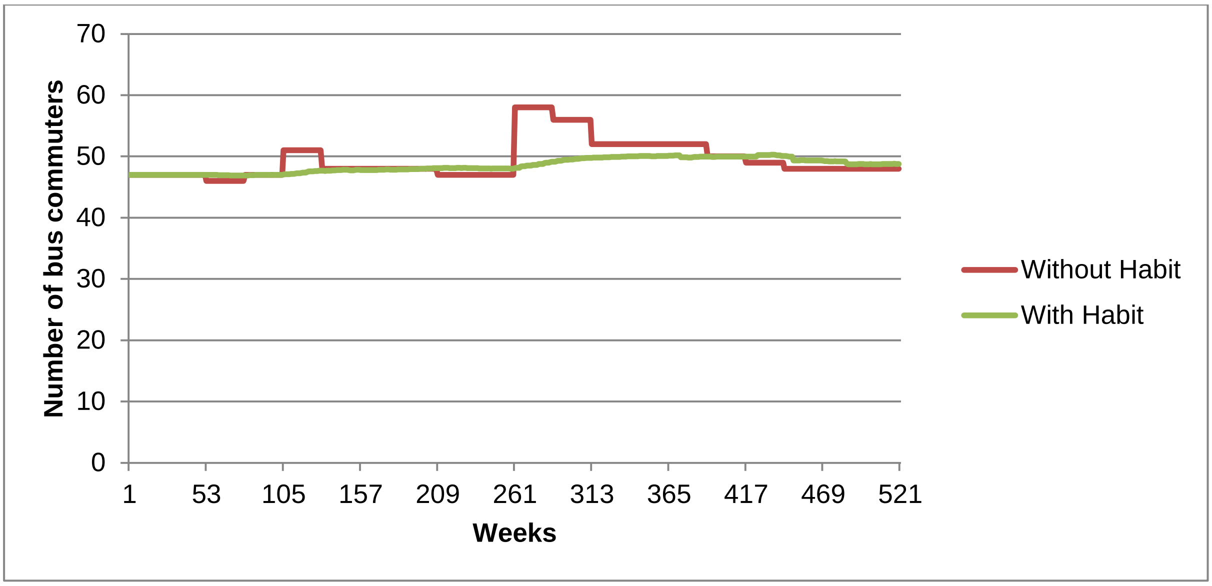

Figure 4: Number of bus commuters with introduction of periodic increases in parking charges

Bus fare elasticities

The lag in response of users to changes in costs was noted in a study into the length of time over which bus passenger numbers respond to a rise in bus fares. Dargay and Hanly. (1999) conducted a dynamic econometric study into bus fare elasticities in the UK using data from the mid-1970s to the mid-1990s. They estimated short-run (1 year) bus fare elasticities for full-fare passengers of between -0.2 and -0.3 and long-run elasticities after around 7 years of -0.7 to -0.9. A typical curve for these elasticities from Dargay and Hanly shows a change in elasticity from -0.4 to -0.9, is shown in Figure 5 below.

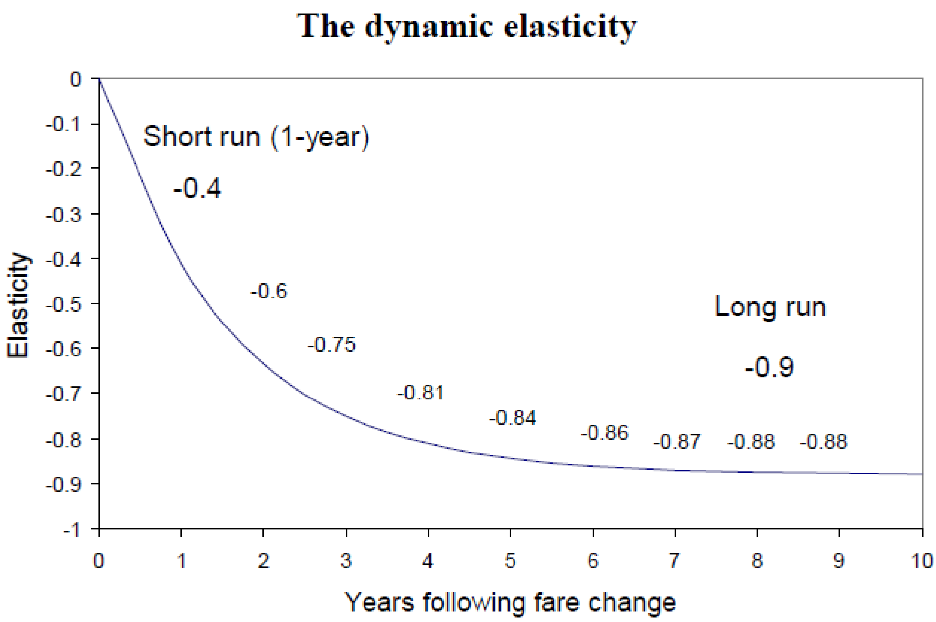

Figure 5: Typical transition from short to long run bus fare elasticities over time

Source: Dargay and Hanly (1999)

The ABM was used to test the elasticity of the response of passenger numbers to a rise in bus fares by keeping the cost of all modes constant throughout the ten year modelled period, with the exception of a 10% bus fare increase at the end of year 2. The forecast number of bus commuters is shown in Figure 6 below.

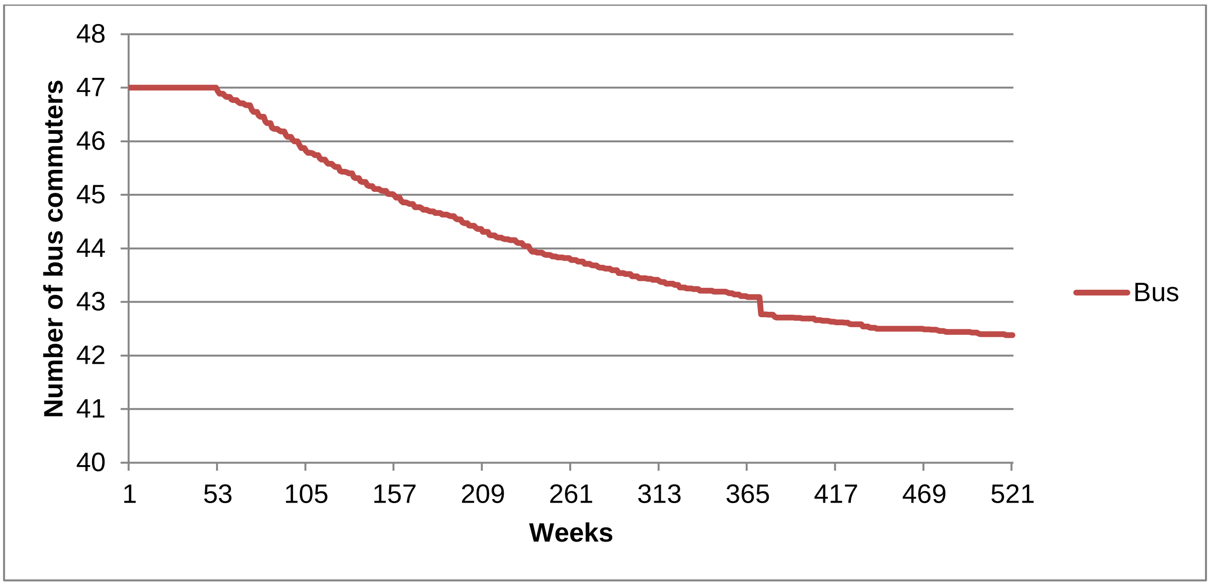

Figure 6: Modelled number of bus commuters following a 10% increase in bus fares

It is clear from the figure that with the inclusion of habit, the ABM predicts a gradual decline in use over years rather than a stepwise reduction. The bus fare elasticities from the model are presented in Table 1 below. The short-run elasticity, produced as an output from the model was -0.25 after 1 year and the long-run elasticity after 7 years was -0.93, which matches well with Dargay and Hanly's estimates. The shape of the change in elasticity over time also mirrors that found in the Dargay and Hanly study. Hence pattern validity (Thorngate, 2013) is shown for the ABM model which includes habits and suggests that the introduction of habitual behaviour produces a model that better represents the observed world than the standard economic model, fulfilling a key objective of the behavioural economics approach.

Table 1: Bus fare elasticities from ABM

Year	Elasticity
1	-0.251
2	-0.428
3	-0.572
4	-0.685
5	-0.768
6	-0.832
7	-0.932

Impact of concessionary bus fares

The agent based modelling methodology has additional advantages that make the method particularly suited to modelling sustainable transport policies. Two of these aspects are highlighted here: the use of the actual costs faced by each individual and the inclusion of feedbacks into the modelling. Figure 7 below compares the predicted number of bus passengers, with habits incorporated into the model, with and without the Welsh policy of providing free bus passes (concessionary bus fares), which are valid at all times of the day, to people over the age of 60. The provision of the free bus pass mitigates the impact of the relative rise in the cost of bus travel over car for some of the agents, and results in a rise rather than a fall in the number of bus passengers, as the ageing of the workforce means that more commuters become eligible for a bus pass.

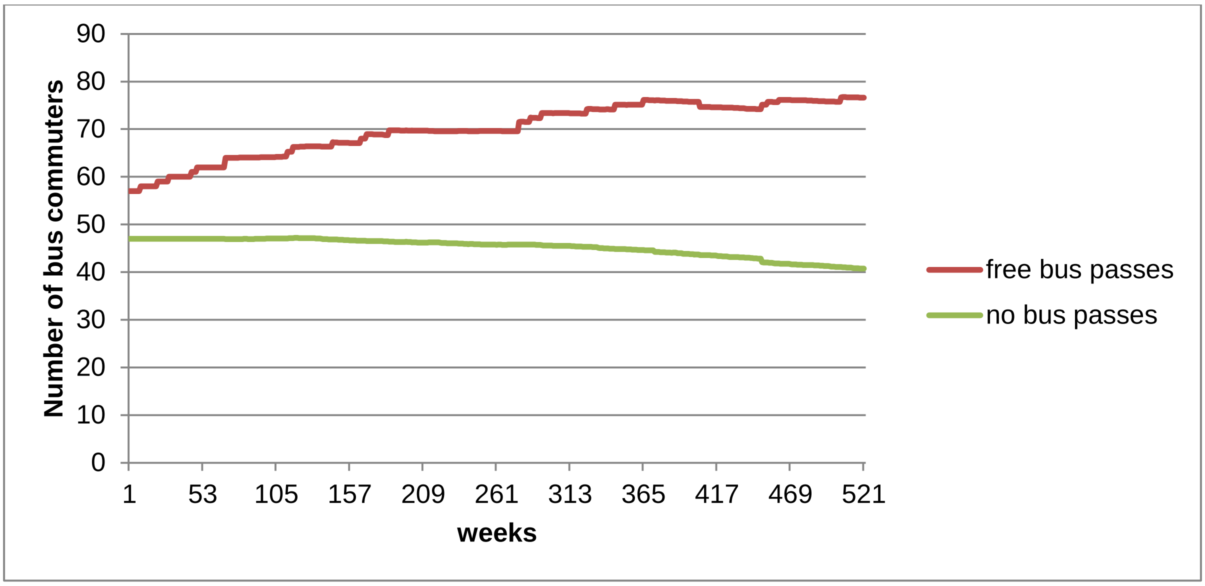

Figure 7: Number of bus passengers with and without concessionary fares

Feedback from demand to supply

The agent based modelling approach readily allows for the inclusion of feedback loops into the model, with bus operators evaluating the financial viability of their services every three months. If the number of passengers falls below a threshold value, given as an input into the model, the service is withdrawn. This affects the state of the facilitating condition of an available bus service for agents served by that route. A reduction in the total number of bus users over time leads to the withdrawal of a service and people who would otherwise have used this unprofitable service have to switch to alternative modes. The output from a model run which included this feedback loop is shown in Figure 8 below. The model was run using current trend values for public transport fares and motoring costs in Wales and illustrates how the model can reproduce the ‘vicious’ circle of decline in bus patronage that has been seen in practice in many areas such as Wales.

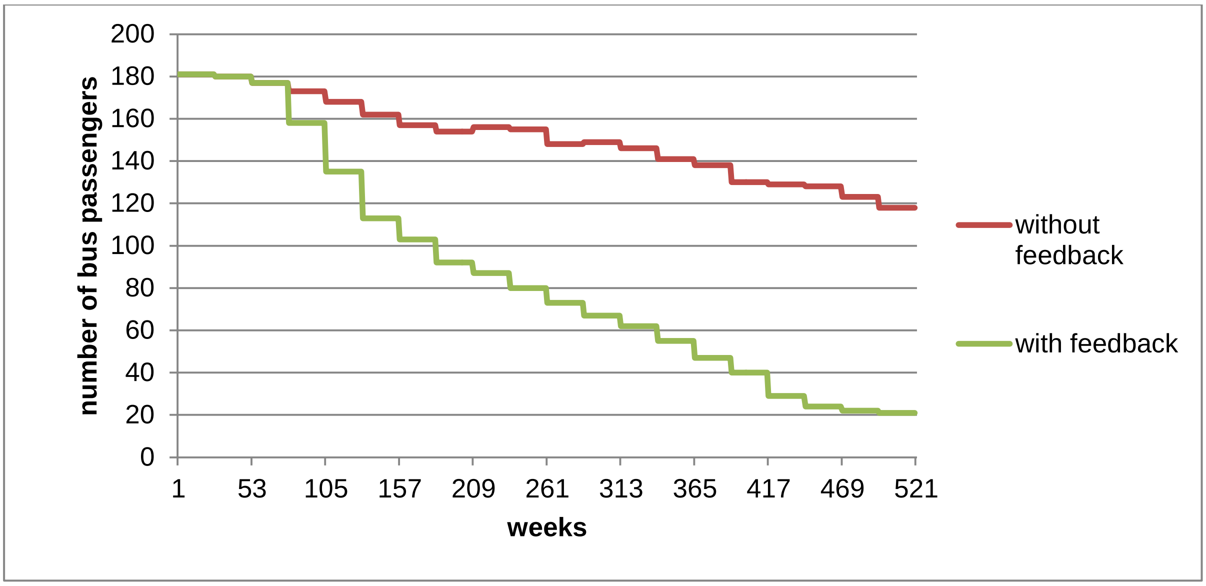

Figure 8: Number of bus passengers with and without feedback, without concessionary fares

The model was also run with and without concessionary bus passes for the elderly, as shown in Figure 9 below. The availability of concessionary fares does not remove the decline in the number of bus services over time but does reduce the rate of decline and the number of buses in the final stable network is higher. This illustrates the indirect benefit of the concessionary fares policy in making more bus services available to those under 60 than would otherwise be the case (although this is not to suggest that current concessionary fares policy is necessarily the most efficient way to provide network-level subsidy for bus services).

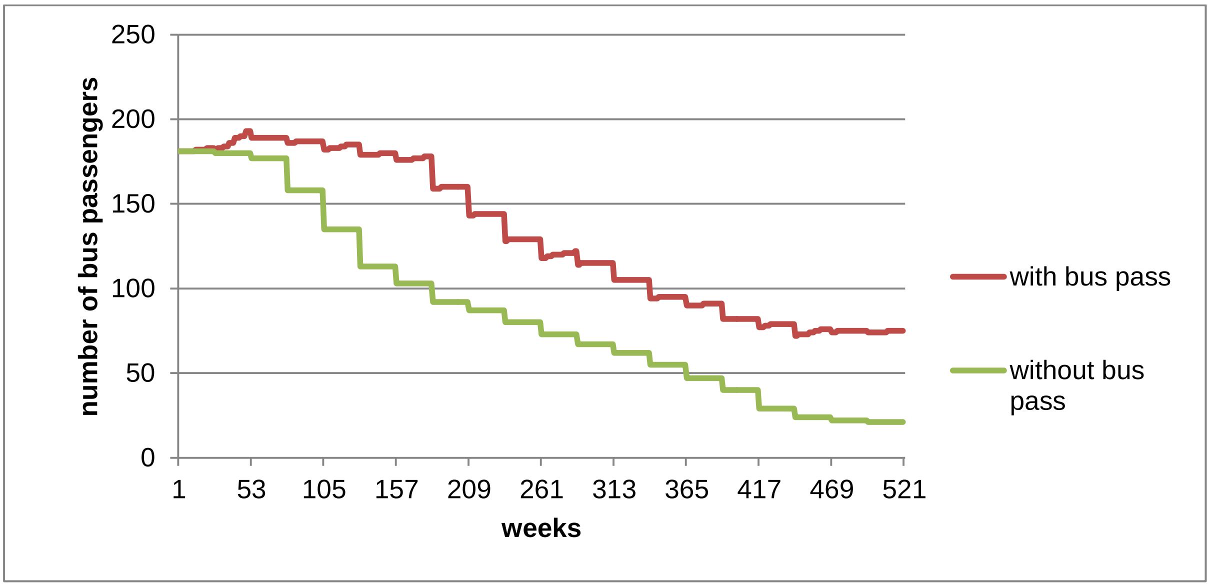

Figure 9: Number of bus passengers, with feedback, with and without concessionary fares

6. Application to Different Study Areas

A policy maker will be concerned with making forecasts for the particular study area of interest to him or her. Information on the time and cost of travel by alternative modes in an area can be calculated using mainstream transport modelling models (i.e. network assignment models). A model of commuter mode choice will also require a database of the people or agents in the area, together with the characteristics of their current and alternative commute journeys as well as their personal attributes and constraints such as age and gender, location of home and work, personal mobility issues and proximity to the public transport network. There is a trend in recent years for ABMs to become more 'empirically grounded' (Rounsevell *et al.*, 2012) and use can be made of techniques developed in the areas of spatial microsimulation and activity-based modelling to develop a synthetic population of the study area. (Beckman *et al*., 1996, Huang *et al.,* 2001).

Therefore, an ABM model generally requires more preparation than is often undertaken in the construction of a standard four-stage transport model but it provides many benefits when the resulting model is used to forecast the impact of sustainable transport policies. These policies are often targeted at specific groups of people and often deal with small numbers, which makes accuracy in forecasting particularly important. Walking and cycling schemes are often justified on the basis of large health benefits to a few people, so having accurate forecasts of the number of people receiving the benefit is crucial. Many bus services in the UK have only a few passengers, so accuracy in forecasting is critical to the development of a robust business case.

The disaggregate level of modelling used in the ABM approach will reduce the level of aggregation bias in the model forecasts produced when average costs are used rather than the specific costs faced by each individual (Castiglione *et al.,* 2014, Haining, 2003). The knowledge of the facilitating conditions for an individual should also improve the accuracy of forecasts, as it enables the use of more realistic choice sets for each person.

Aggregation bias also occurs in standard mode choice models through the use of a shared preference function which provides the weighting applied to the time and cost elements of each journey option when calculating their utility to the commuter. This is a recognised source of inaccuracy in model outputs in the economics literature on the link between micro and macroeconomic models, where it is known as the representative agent problem (Kirman 1996, Gorman 1953).

It is not feasible to survey each individual to determine his or her own preference function but it is possible to group people together into a larger number of groupings than is used in standard, matrix based, mode choice models, which often only use only two segments for commuting trips based on car availability or not. Latent class analysis (McCutcheon, 1987) is ideally suited to the task of identifying these segments as it provides a method for grouping agents together based on their shared preferences for mode, time and cost of travel.

A latent class analysis of the 626 agents in the DfT survey was undertaken using Sawtooth software. This identified five classes of people including a group of car lovers (15%), time critical commuters (33%) and confirmed cyclists (13%). The results are presented in Table 2 below. Statistical analysis using CHAID techniques can then be used to identify the observable characteristics of the population, which can be used as indicators to place members of the synthetic population into the appropriate latent class.

Table 2: Latent Class Analysis for respondents to DfT survey

		Class 1	Class 2	Class 3	Class 4	Class 5
Number of respondents		**14.80%**	**6.50%**	**33.00%**	**32.70%**	**13.10%**
Mode	**Bus**	-81.17	117.28	20.85	-18.28	-38.42
	Car	213.31	-103.56	67.65	18.76	-24.07
	Train	-57.47	74.17	38.33	-10.56	-52.40
	Cycle	-74.66	-87.89	-126.83	10.08	114.90
Cost	**£1.50**	-2.72	24.21	16.09	24.51	29.01
	£2.00	5.85	-19.08	8.03	7.83	19.56
	£2.50	5.84	16.74	-8.45	-10.32	-17.25
	£3.00	-8.98	-21.87	-15.67	-22.02	-31.33
CO2	**1 kg**	8.98	15.25	11.18	13.75	18.36
	2 kg	-1.58	4.04	1.21	5.21	9.69
	3 kg	9.76	-23.97	-4.87	-0.44	-14.15
	4 kg	-17.16	4.68	-7.52	-18.52	-13.90
Time	**15 min**	36.46	42.24	80.41	146.55	63.87
	30 min	16.54	25.37	32.45	74.16	43.07
	45 min	-20.66	1.19	0.05	-6.83	16.68
	60 min	-5.05	-17.17	-38.26	-76.27	-47.64
	75 min	-27.30	-51.62	-74.65	-137.61	-75.98

The importance of aggregation bias due to the use of a single preference function for many agents is shown in Figure 10 below. The maximum utility behavioural rule is no longer suitable when latent classes are used to derive preference functions for each agent as there will be sudden jumps in the number of agents using a particular mode when a whole group change at one time. This effect can be reduced by using a logit model to predict the probability of an agent choosing a particular mode in each time period (if they are not using their habitual mode) and then comparing this with a random number to allocate that agent to a particular mode.

The ABM was run, with habitual behaviour and several increases in parking charges, to illustrate the impact of aggregation bias from the use of a single preference function for many agents caused by having the modelled population placed into only a few segments. For each time period in the model run, the mode chosen was recorded for each agent with their individual preference function used, that of their latent class or the preference function for the two commonly used segments; car available/ non available. The forecast number of bus passengers shown in Figure 10 below reflects the use of a model incorporating habitual behaviour and the presence of concessionary bus passes for the over 60s. The difference in passenger numbers is considerable: up to 35% in year 10 between using individual preference functions and the standard car available/non-car available segmentation. This suggests that aggregation bias could be contributing to the over-optimistic forecast of bus passengers in standard transport models and that this could be reduced significantly by using an individual preference function.

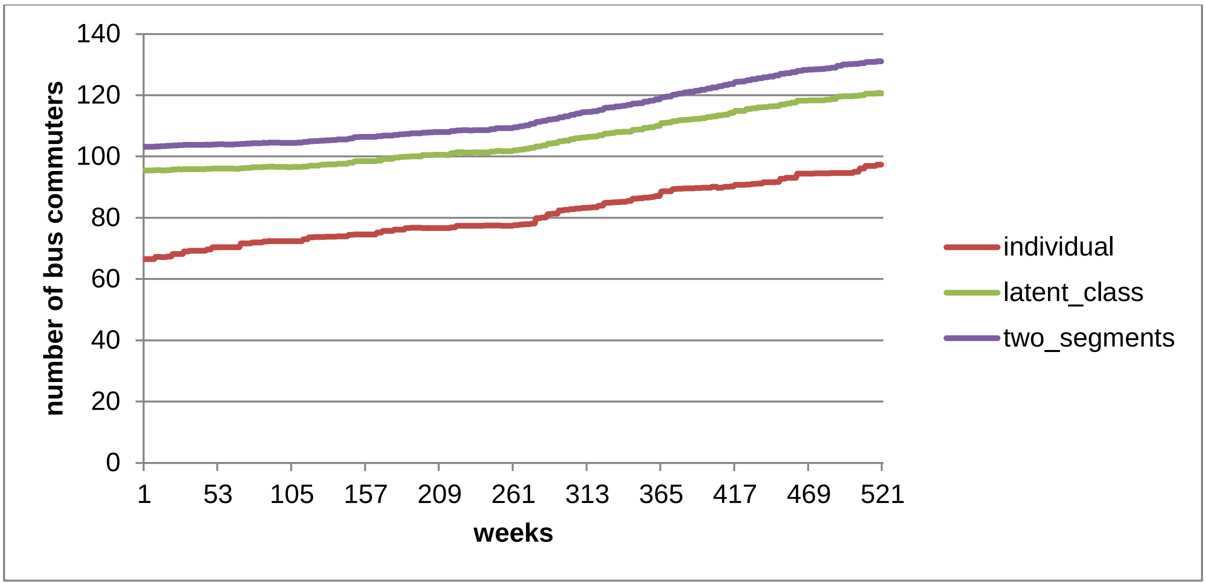

Figure 10: Forecast number of bus commuters using individual, five latent class or two car available/ non-car available segments

7. Conclusions

The objective of this study was to improve the accuracy of the forecasts produced of the impact of a variety of sustainable transport policies on the mode of travel used by commuters. The common approach in transport models is to use a mode choice model built within the established standard neo-classical economic framework, with its assumptions of perfectly rational behaviour, perfect knowledge and a common preference function for all people within the same coarse segment.

The behavioural economics approach is to bring a greater degree of psychological realism into neo-classical economic models. In this example, habitual behaviour was included which resulted in a lagged response to changes in the time and cost of travel by alternative modes. This was implemented in an agent based model which provides a dynamic model of the change in passenger numbers as a response to policy changes. The greater detail of these forecasts will be beneficial to policy makers, particularly if they need to consider the financial implications of proposed policies. There are also implications for evaluation studies, as the dynamic model provides forecasts of the change expected over time as a result of a policy which can be compared to evaluations undertaken both shortly after implementation and after longer intervals.

The use of an agent based methodology increased the range of policies that the model can test. The model can assess policies which affect the cost of travel for very specific groups (and which affect them differently over time), for example discounted or free fares for the elderly, changes in the age at which concessionary bus passes are provided to the elderly and the extent of the discount to fares provided. The model can also be used to test policies that aim to influence travel modes by affecting the 'facilitating conditions' for example 'dial a ride' bus services for people with mobility issues or the provision of low-floor, easy-access buses. It can also model feedbacks within the system, for example with lower public transport patronage leading to fewer or less frequent bus services.

This behavioural economics mode choice model can be implemented within a standard trip or tour based four-stage modelling framework. This allows widely adopted transport modelling software to be used for the calculation of journey times and costs, which are used as inputs to the mode choice model. The use of individual time and cost inputs and more finely segmented groups with shared preference functions provides a means of reducing the level of aggregation bias in current models. This is particularly significant when dealing with the small numbers often involved in changes brought about by sustainable transport policies. The agent based modelling approach also allows for the further incorporation of insights from behavioural sciences into mode choice modelling, such as the influence of the opinions and behaviours of peers on the agents' intended behaviour.

References

Aarts, H., and Dijkesterhuis, A., (2000) The automatic activation of goal-directed behaviour: the case of travel habit. *Journal of Environmental Psychology, 20, 76-82.*

Bamberg, S. (2006) Is a residential relocation a good opportunity to change people's travel behaviour? Results from a theory-driven intervention study. *Environment and Behaviour 38 820 – 840.*

Beckman, R. , Baggerly, K. , & McKay, M. (1996). Creating synthetic base-line populations. *Transportation Research A, Policy and Practice, 30, 415-429.*

Brown, B., Werner C. and Kim, N., (*2003)* 'Personal and contextual factors supporting the switch to transit use: evaluating a natural transit intervention', *Analyses of Social Issues and Public Policy, 3 (1), pp. 139 – 160,*

Camerer (2003) *Advances in Behavioural Economics* (Camerer, Loewenstein, Rabin, Editors), Princeton University Press

Castiglione J., Bradley M., and Gliebe J. (2014) Activity-Based Travel Demand Models: A Primer. *The Strategic Highway Research Program of the Transportation Research Board.*

Chatterjee, K., Sherwin, H. and Jain, J. (2013) Triggers for changes in cycling: The role of life events and modifications to the external environment. *Journal of Transport Geography*, *30. pp. 183-193.*

Clark, B., Chatterjee, K., Melia, S., Knies, G. and Laurie, H. (2014) Life events and travel behaviour: Exploring the interrelationship using UK household longitudinal study data. *Transportation Research Record, 2413. pp. 54-64.*

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

Department for Transport Statistical data set Costs, fares and revenues Table BUS0415

Department for Transport WebTAG Unit A1.3 User and Provider Impacts (2014)

Fujii, S., Garling, T. and Kitamura, R. (2001) Changes in Drivers' Perceptions and Use of Public Transport during a Freeway Closure: Effects of Temporary Structural Change on Cooperation in a Real Life Social Dilemna. *Environment and Behavior Vol 33.*

Gardner, B. (2009) Modelling motivation and habit in stable travel mode contexts. *Transportation Research Part F. 12 p 68 – 76.*

Garling, T., Fujii, S., and Bie, O. (2001) Empirical tests of a model of determinants of script-based driving choice. *Transportation Research Part F* 4 (2) 89 – 102.

Gorman, W. (1953), "Community preference fields", *Econometrica, 21, 63-80.*

Haining, R. (2003) *Spatial Data Analysis: Theory and Practice.* Cambridge University Press.

Huang Z and Williamson P (2001) Comparison of synthetic reconstruction and combinatorial optimisation approaches to the creation of small-area microdata. *Working Paper 2001/2, Population Microdata Unit, Department of Geography, University of Liverpool, Liverpool.*

Jackson, T. (2005) Motivating Sustainable Consumption*. Centre for Environmental Strategy University of Surrey.*

Kirman, A. (1992) Whom or What Does the Representative Individual Represent? *The Journal of Economic Perspectives, Vol. 6, No. 2.*

Klockner, C. and Matthies, E. (2004) How habits interfere with norm-directed behaviour: A normative decision-making model for travel mode choice. *Journal of Environmental Psychology 24, 319-327.*

McCutcheon, A. (1987) *Latent class analysis*. Beverly Hills: Sage Publications.

OECD (2013), "Labour Market Statistics: Employment by job tenure intervals: average tenure", *OECD Employment and Labour Market Statistics* (database). doi: 10.1787/data-00294-en (Accessed on 28 September 2013).

O'Sullivan, D. and Haklay, M. (2000) Agent-based models and individualism: is the world agent-based? *Environment and Planning 328 1409 – 1425.*

Prillwitz, J. and Lanzendorf M., (2006) The Importance of Life Course Events for Daily Travel Behaviour – A Panel Analysis, paper presented at the 11th International Conference on Travel Behaviour Research, Kyoto, August 2006.

Rounsevell, M., Robinson, D., and Murray-Rust, D., (2012) From actors to agents in socio-ecological systems models. *Philosophical Transactions of the Royal Society.*

Thorngate, W. and Edmonds, B. (2013) 'Measuring Simulation-Observation Fit: An Introduction to Ordinal Pattern Analysis'. *Journal of Artificial Societies and Social Simulation 16 (2).*

Teahan, W. (2010) Artificial Intelligence – Agents and Environments. Ventus Publishing.

Thornton, A., Evans, L., Bunt, K., Simon, A., King, S. and Webster, T. (2011). Climate Change and Transport Choices. Segmentation Model - A framework for reducing CO_2 emissions from personal travel.

Triandis, H. (1977) Interpersonal Behaviour. *Monterey, CA: Brooks/Cole.*

University of Essex. Institute for Social and Economic Research, *British Household Panel Survey: Waves 1-18, 1991-2009* [computer file]. *7th Edition.* Colchester, Essex: UK Data Archive [distributor], July 2010. SN: 5151, http://dx.doi.org/10.5255/UKDA-SN-5151-1

Van der Waerden, P., Timmermans, H., and Borgers, A., (2003) The influence of key events and critical incidents on transport mode switching behaviour: a descriptive analysis. *Presented at the 10th international conference on travel behaviour research. Lucerne 2003.*

Verplanken, B., Aarts, H., and van Knippenberg, A. (1997) Habit and information use in travel mode choices. *Acta psychological.* 96 1-14.

Verplanken, B., Walker, I., Davis, A. and Jurasek, M., (2008). Context change and travel mode choice: Combining the habit discontinuity and self-activation hypotheses. *Journal of Environmental Psychology*, 28 (2), 121-127.