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Jennifer Roberts, Gurleen Popli, Rosemary J. Harris

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Do environmental concerns affect commuting choices?

Hybrid choice modelling with household survey data

Jennifer Roberts[1], Gurleen Popli[1], Rosemary J. Harris[2]

[1] Department of Economics, University of Sheffield,
[2] School of Mathematical Sciences, Queen Mary University of London

October 2014

Abstract

In order to meet their ambitious climate change goals governments around the world will need to encourage behaviour change as well as technological progress; and in particular they need to weaken our attachment to the private car. A prerequisite to designing effective policy is a thorough understanding of the factors that drive behaviours and decisions. In an effort to better understand how the public's environmental attitudes affect their behaviours we estimate a hybrid choice model (HCM) for commuting mode choice using a large household survey data set. HCMs combine traditional discrete choice models with a structural equation model to integrate latent variables, such as attitudes and other psychological constructs, into the choice process. To date HCMs have been estimated on small bespoke data sets, beset with problems of sample selection, focusing effects and limited generalizability. To overcome these problems we demonstrate the feasibility of using this valuable modelling approach with nationally representative data. Our estimates suggest that environmental attitudes and behaviours are separable constructs, and both have an important influence on commute mode choice. These psychological factors can be exploited by governments looking to add to their climate change policy toolbox in an effort to change travel behaviours.

JEL Codes: C38; Q50; R41

Key words: hybrid choice model, structural equation modelling, environment.

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1. Introduction

Tackling climate change is one of the most important challenges faced by governments around the world. The US has committed to reducing greenhouse gas emissions by 17 % below 2005 levels by 2020, and in the UK the Climate Change Act 2008 commits the government to cut emissions by at least 80% by 2050. Achieving these targets will not be possible via technical progress alone; it will also require substantial behaviour change on the part of individuals and households. A prerequisite to designing effective policy interventions is a thorough understanding of the factors that drive behaviours and ultimately decisions. One topic that has been the subject of much discussion is the extent to which individual environmental concerns can motivate behaviour change. The majority of the literature is pessimistic in this regard; while the public express concern about climate change, this is rarely strong enough to bring about change towards more sustainable behaviours, especially when these changes require personal sacrifice (Gifford, 2011). Nowhere is this more apparent than in our seemingly unshakeable attachment to the private car.

In this paper we use hybrid choice modelling to explore the effects of environmental concerns on choice of commuting transport mode in England. HCMs combine traditional discrete choice models (DCMs) with a structural equation model (SEM) to integrate latent variables, such as attitudes and other psychological constructs, into the choice process. Our overall aim is to improve our understanding of the way that people make travel choices; and we make three main contributions to the literature. Firstly, our study is a rare example of one which attempts to evaluate the importance of environmental beliefs for travel behaviours. Secondly, a major innovation is the use of a large nationally representative household survey data set for model estimation; we also replicate the modelling with a second such dataset, as a robustness check on the results. To date HCMs have been estimated using relatively small data sets constructed to tackle the question in hand. These bespoke data have limited generalizability, are prone to substantial selection problems and focusing effects, and include little information on individual characteristics with which to control for heterogeneity. Thirdly, HCM studies of mode choice generally

devote little or no attention to the theoretical model of decision making that underlies the empirical work; in contrast we explain how the *attitude-behaviour-context* (ABC) model (Stern, 2000; Stern and Oskamp, 1987) is an appropriate framework for our HCM of commuting mode choice incorporating latent environmentalism.

Domestic transport accounts for 25% of the UK's CO_2 emissions, more than half of which are from the private car[1]. Thus meeting climate change goals necessitates a shift away from the car and towards more sustainable modes such as public transport, walking and cycling. The regular commuting journey is a key arena in which to study these choices; 57% of all commute trips are by car[2]. A recent report for the UK Department of Transport reveals that the implications of climate change are not widely understood and that most people are unaware of their own contribution to the problem (King et al., 2009). However, knowledge alone is not an adequate antecedent to behaviour change; in their systematic review of interventions to reduce car use Graham-Rowe et al. (2011) find no evidence that providing environmental information is effective.

Traditionally transport choice modelling has employed discrete choice models (DCMs); these are based in random utility theory (RUT), an economic framework in which time and cost are the key variables (see for example Train, 1980). RUT has been criticised for its fundamental assumption that consumers are a rational "optimizing black box" (Morikawa et al., 2002). HCMs were first proposed as an extension to RUT in the 1980s, as a way of better understanding consumer behaviour by incorporating latent variables, such as preferences and attitudes, into the choice process (McFadden, 1986; Ben-Akiva and Boccara, 1987). More broadly HCMs can be seen as a reflection of the growing popularity of behavioural economics, which incorporates psychological concepts into economic analysis in order to improve our understanding of decision making under uncertainty (Tversky and Kahneman, 1974).

Empirical applications of HCMs have developed largely from 2000 onwards. Morikawa et al., (2002) find a significant influence of latent variables for comfort and convenience on the decision to use rail or car for intercity travel between cities in the Netherlands. Temme et al. (2007) find that latent preferences for

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comfort, convenience, flexibility and safety affect the travel mode choices of a market research survey panel in Germany. Yáñez et al. (2010) consider the effects of three latent variables (accessibility, reliability and comfort) on commute mode following the introduction of a new urban transport system in Santiago, Chile. Córdoba and Jaramillo (2012) demonstrate the importance of a 'personality measure' on the commute mode choices of staff at the National University of Columbia.

Johansson et al. (2006) is the only HCM study that we know of that has incorporated any measure of environmentalism into a mode choice model. Data are from a postal survey of commuters in Sweden, and the environmentalism variable is inferred from measures of the frequency with which the respondents recycle glass, paper, batteries and metal. This variable is found not to be significant in the choice of car versus bus but has marginal significance in the train/bus choice. This neglect of environmental variables is a serious shortcoming given the key role of personal travel choices in climate change. Environmental attitudes are likely to influence the utility that an individual derives from different travel modes, and hence ultimately may affect mode choice. The relative importance of environmental attitudes alongside other influences such as fiscal incentives is of key interest to policy makers.

2. Decision Making Model

Existing empirical applications of HCMs tend not to be based in clear theoretical frameworks and thus it is often difficult to interpret the results, especially in relation to inferring causal relationships. This is particularly problematic for SEMs, because these models do not provide a means of establishing causality but rather are only able to confirm relationships that the researcher must impose from external knowledge (Sánchez et al., 2005; Bollen and Pearl, 2013). Environmental concerns reflect how we feel about the environment and the way we are predicated to behave with regard to it. These are complex phenomena that combine elements of pro-social preferences, risk and time preference, selfish regard for one's own (and one's children's) future, social pressures and norms. 'Environmentalism' is mediated by knowledge and institutions, which influence the immediate costs to individuals; it also involves interaction between attitudes and behaviours.

In our HCM we propose that 'environmentalism' is a latent construct that we cannot observe directly. Instead it is represented by a set of observable indicators that measure both *attitudes* towards the environment and climate change, as well as certain environmental *behaviours*; these behaviours are not directly related to commuting, but relate to other areas of life such as recycling, and use of carrier bags and home energy. These indicators are used in an SEM, which is combined with a DCM to integrate the latent variable(s) for 'environmentalism' into a model for commuting mode choice.

The psychological literature explains that attitudes and behaviours are related but theoretically distinct. A *behaviour* is an observable action; for example switching a tap off rather than letting it drip, or putting on an extra jumper rather than turning the heating up. *Attitudes* are the subjective importance attached to different issues; for example the extent to which a person believes that climate change is a cause for concern, or the extent to which they believe that the environmental crisis has been exaggerated. The attitude-behaviour relationship is a core topic in psychology (Kraus, 1995); in general it is understood that behaviours are driven by intention, and intention is, in turn, a function of attitudes (Ajzen and Fishbein, 1977). For example, people with pro-environmental attitudes might have a strong intention not to use the car for short trips and hence act in a way that is consistent with this, choosing instead to use public transport or walk/cycle. However, there may also be discrepancies between attitudes and behaviours (Ajzen and Fishbein, 1970) and this has gained empirical support within the environmental context (Oskamp et al., 1991; Gardner and Abraham, 2008).

Kline (1988) stresses the importance of contextual factors that can weaken the attitude-behaviour connection, arguing that people will be less willing to act in a pro-environmental way when this is costly or inconvenient, or when they do not feel that their personal contribution can make much difference[3] and when they perceive that others are not behaving that way (Oskamp et al., 1991). Also, many people believe that the government is responsible for solving environmental problems and rely on this to justify their own behaviours (Stern et al., 1985). While it is usually thought that attitudes precede behaviour, behaviours can change attitudes; for example, individuals with pro-environmental beliefs who

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[3] Crompton (2010) describes these as 'bigger than self' problems; where the return on personal effort is unlikely to justify the expenditure of resources required to tackle the problem.

nevertheless use the car for short trips might change their attitudes in an attempt to rationalise their mode choice and reduce cognitive dissonance (Festinger, 1962).

There are a number of theoretical models of decision making that support the integration of psychological variables into transport mode choice models. Gardner and Abraham (2010) test Ajzen's (1991) *theory of planned behaviours* (TPB) for local car use in a small UK city (Brighton and Hove). Bamberg and Schmidt (2003) compare TPB with the *theory of interpersonal behaviour* (Triandis, 1977) and the *norm activation model* (Schwartz, 1977) for car use in a student sample. Neither of these studies finds much support for the influence of environmental attitudes; perceived personal benefits such as convenience outweigh environmental opinions and car use is so habitualised that there is little or no moral dimension to the choice.

The *attitude-behaviour-context* (ABC) model (Stern, 2000; Stern and Oskamp, 1987) was developed specifically to explain environmentally significant behaviours and provides an ideal theoretical framework for our HCM of commuting mode choice. Behaviour in this model is an interactive product of 'internal' attitudes, such as concerns over climate change, and 'external' contextual factors such as the transport costs, and institutional constraints such as the local availability of transport choices. Hence external factors (like time and cost) will moderate the effect of environmental beliefs, and the relative importance of psychological and contextual factors will depend on the behaviour in question. Attitudes have been found to have stronger effects for low-constraint behaviours that are cheap or easy to change, such as curb-side recycling or the use of low-energy light bulbs (Stern and Oskamp, 1987; Guagnano et al., 1995). We would expect them to have less influence on behaviours like car use, which have high personal benefits, are habitualised and are seen as difficult to change (Collins and Chambers, 2005). Nevertheless the relative influence of these different sets of factors is a key issue for designing policies to change behaviours, and this is where our study can make a clear contribution.

A schematic of our HCM is shown in Figure 1; this illustrates how a traditional DCM is combined with a latent variable model for 'environmentalism'. The unobservable latent variable(s) for 'environmentalism' are identified via observed indicators that reflect environmental *attitudes* or *behaviours*; the number of latent

variables and the classification of indicators is determined via both exploratory and confirmatory factor analyses, as explained in the next section. 'Environmentalism' is also determined by observed socio-demographic characteristics such as age, sex and household income; these are important *context* variables, for example whether or not the individual has young children will influence how much personal (in)convenience they might experience from using public transport rather than a car. Latent utility from commuting mode is determined by 'environmentalism', and also directly by socio-demographic variables and the key mode attributes of time and cost, which are again important measures of *context*. We observe the final mode choice decision as a manifestation of the underlying latent utility. The statistical basis of this model and its estimation are explained in the next section.

3. Specification and Estimation of Hybrid Choice Model

3.1 Structural Model

u_{ij}^* is the unobserved (latent) conditional indirect utility for mode j ($j = 0, \ldots, J-1$) for individual i ($i = 1, \ldots, n$). In the empirical analysis we assume a linear in parameters specification:

$$(1) \qquad u_j^* = \boldsymbol{x}'\beta_{jx} + \boldsymbol{z}'\beta_{jz} + \boldsymbol{\eta}'\beta_{j\eta} + v_j$$

where u_j^* is an $(n \times 1)$ column vector of individual utilities; x_i is a $(K_x \times 1)$ vector of K_x individual specific observed variables, such as age and income, and $\boldsymbol{x}$ is a $(K_x \times n)$ matrix obtained by horizontal concatenation of x_i; z_i is a $(K_z \times 1)$ vector of observed *context* variables for individual i, relating to mode, such as availability of local public transport, and $\boldsymbol{z}$ is a $(K_z \times n)$ matrix obtained by horizontal concatenation of z_i; η_i is a $(Q \times 1)$ vector of Q individual specific latent variables, which represent the unobservable 'environmentalism' of the individual (environmental *attitudes* and *behaviours*), and $\boldsymbol{\eta}$ is a $(Q \times n)$ matrix obtained by horizontal concatenation of η_i; β_{jx}, β_{jz}, and $\beta_{j\eta}$ are $(K_x \times 1)$, $(K_z \times 1)$ and $(Q \times 1)$, respectively, vectors of parameters to be estimated; and v_j is an $(n \times 1)$ column vector of

random error terms. The latent variables in matrix $\boldsymbol{\eta}$ are also assumed to depend linearly on the vector of individual specific observed variables:

(2) $$\boldsymbol{\eta} = \boldsymbol{\gamma}'\boldsymbol{x} + \boldsymbol{\xi}$$

where $\boldsymbol{\gamma}'$ is a $(Q \times K_x)$ matrix of parameters to be estimated and $\boldsymbol{\xi}$ is a matrix of $(Q \times n)$ random error terms.

3.2 Measurement Model

We do not observe u_{ij}^*, what we observe is the choice made by the decision maker whether to use mode j or an alternative l, $(j, l \in J)$. The observed decision variable is defined as:

$$d_i = j \quad \text{if } u_{ij}^* > u_{il}^*; \ \forall \ l \in J$$
$$d_i = 0 \qquad \text{otherwise}$$

In our empirical analysis $J = 2$; the individual either commutes by car $(j = 1)$ or by public transport $(j = 0)$, so without loss of generality we can assume $u_{i0}^* = 0$. In subsequent discussion we suppress the indexation for the mode. The decision of the individual is modelled as:

(3) $$P(d_i = 1) = P(u_i^* > 0) = P\left(v_i > -x_i'\beta_x - z_i'\beta_z - \eta_i'\beta_\eta\right)$$
$$= 1 - F(-x_i'\beta_x - z_i'\beta_z - \eta_i'\beta_\eta)$$

Where $F(.)$ is the cumulative distribution function for the measurement error v. We treat $F(.)$ as a normal distribution, and therefore estimate a probit model; however a logit model, based on the logistic distribution, produces very similar results.

Let $\boldsymbol{\eta}' = [\eta^1, \dots, \eta^Q]$, where η^q is a $(n \times 1)$ vector which contains as components the latent variables for all the individuals. We do not directly observe η^q $(q \in Q)$, what we do observe are different indicators for η^q. So for example, we do not observe directly how 'green' people are, what we do observe are their responses to questions reflecting their environmental *attitudes* and *behaviours*, and these can be considered indicators of their underlying 'environmentalism'. Let Y_s^q be an $(n \times 1)$ vector of the

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indicators for η^q, where $s = 1, \dots, m^q$, such that $m^q \geq 2$ i.e. we need a minimum of two indicators for each latent variable. The observed indicators are related to the unobserved latent variable as:

(4) $$Y_s^q = \mu_s^q + \alpha_s^q \eta^q + \varepsilon_s^q \qquad \forall \quad q \in Q \;\; \text{and } s \in m^q$$

where the number α_s^q is the factor loading from the factor analysis, which can be interpreted as the amount of information that the indicator Y_s^q contains about η^q; ε_s^q is an $(n \times 1)$ vector of measurement errors, which captures the difference between the observed indicators and the unobserved variable; and the intercept μ_s^q is an $(n \times 1)$ vector with all elements equal, i.e., no dependence on individual.

We have a set of measurement equations, similar to equation (4) for each of the latent variables in the matrix $\boldsymbol{\eta}$. In matrix notation:

$$Y = \boldsymbol{\mu} + \boldsymbol{\eta}'\boldsymbol{\alpha} + \boldsymbol{\varepsilon}$$

where $\boldsymbol{Y}$ is a matrix of $(n \times M)$ indicators, such that $M = m^1 + m^2 + \cdots + m^q$; $\boldsymbol{\alpha}$ is a matrix of $(Q \times M)$ factor loadings; $\boldsymbol{\varepsilon}$ is an $(n \times M)$ matrix of measurement errors; and $\boldsymbol{\mu}$ is an $(n \times M)$ matrix containing the M intercepts. For example, if we assume $Q = 2, m^1 = m^2 = 2$, then:

$$[Y_1^1 \;\; Y_2^1 \;\; Y_1^2 \;\; Y_2^2] = [\mu_1^1 \;\; \mu_2^1 \;\; \mu_1^2 \;\; \mu_2^2] + [\eta^1 \;\; \eta^2] \begin{bmatrix} \alpha_1^1 & \alpha_2^1 & 0 & 0 \\ 0 & 0 & \alpha_1^2 & \alpha_2^2 \end{bmatrix} + [\varepsilon_1^1 \;\; \varepsilon_2^1 \;\; \varepsilon_1^2 \;\; \varepsilon_2^2]$$

where, as above, $Y_s^q, \eta^q, \varepsilon_s^q$, and μ_s^q are themselves $(n \times 1)$ vectors.

The factor loadings in equation (4) can be identified only up to a scale, so we normalize them according to: $\alpha_1^q = 1 \;\; \forall \; q \in Q$. Further we cannot separately identify the mean of the latent variables, $E(\boldsymbol{\eta})$, and intercepts $\boldsymbol{\mu}$; we need to normalize one of them, we assume $E(\boldsymbol{\eta}) = 0$ and identify $\boldsymbol{\mu}$.

We employ both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to explore and verify the latent variables to be used in our HCM. In the EFA no preconceived structure is imposed, and the indicators are allowed to load freely, thus determining the dimension of matrix $\boldsymbol{\eta}$ (i.e. the value of

Q)[4]. In contrast, in the CFA we constrain the model to comply with prior beliefs based on evidence from the psychological literature that attitudes and behaviours are theoretically distinct. Thus the indicators are split into two vectors ($Q = 2$) according to the question wording, with one set forced to load onto an attitudes factor, and the other onto a behaviours factor. The definitions and split are provided in Appendix 1.

Equations (1) and (3) give the standard DCM, and equations (2) and (4) give the latent variable model; together these equations define the HCM. It is worth pointing out here that an alternative specification to the HCM would be to include the indicator variables, Y, directly into the DCM instead of including the latent variables ($\boldsymbol{\eta}$); this is analogous to treating the indicators as direct measures of environmentalism rather than as functions of it. This is inappropriate for two main reasons; firstly, the indicator variables may be correlated with the errors from the DCM due to omitted (unobservable) effects and this would lead to endogeneity bias; secondly, the latent variables that the indicators represent are measured with error, thus their direct inclusion in the DCM can lead to inconsistent estimates (Ashok et al., 2002). Further, the specification we adopt is a closer representation of the psychological decision making framework; attitudes and related behaviours are not direct antecedents of mode choice, but are indirectly related via, *inter alia*, latent environmental concerns.

3.3 Identification, estimation and diagnostic statistics

To be able to identify the parameters in the system of equations (1) to (4) we need to make the following assumptions:

Assumption 1: The error terms $\boldsymbol{v}$, $\boldsymbol{\xi}$, and $\boldsymbol{\varepsilon}$ are independent of $\boldsymbol{x}$, $\boldsymbol{z}$, and $\boldsymbol{\eta}$

Assumption 2: $E(\boldsymbol{\xi}\boldsymbol{v}) = E(\boldsymbol{\varepsilon}'\boldsymbol{v}) = E(\boldsymbol{\xi}\boldsymbol{\varepsilon}) = 0$, i.e. the errors terms $\boldsymbol{v}$, $\boldsymbol{\xi}$, and $\boldsymbol{\varepsilon}$ are uncorrelated.

Further, define the following variance-covariance matrices:

$$E(\boldsymbol{v}\boldsymbol{v}') = \boldsymbol{\Sigma} \qquad E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \mathbf{E} \qquad E(\boldsymbol{\xi}'\boldsymbol{\xi}) = \boldsymbol{\Xi}$$

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[4] Factor extraction in the EFA is done via varimax rotation (Kaiser, 1958) and model selection criteria and diagnostic statistics are discussed in the Results section.

Assumption 3: $\mathbf{\Sigma}$, $\mathbf{E}$, and $\mathbf{\Xi}$ are diagonal matrices, with off-diagonal elements zero.

We further assume, for estimation, that the error terms ν, ξ, and ε have a multivariate normal distribution. Estimation is carried out using the WLSMV estimator in Mplus v. 7.11[5]. The system of equations (1) to (4) that comprise the HCM are estimated simultaneously. The asymptotically distribution-free weighted least squares (WLS) estimator (Browne, 1984) is chosen over the more commonly used maximum likelihood (ML) approach because the latter requires the indicator variables to be continuous and multivariate normal and this is not the case in our application, as we have a number of dichotomous and ordinal variables (see next section). We cannot rely on the asymptotic properties of WLS when sample size is small but (as described in the next section) our estimation samples are over 6,000, which is unusually large for HCM applications[6]. Given the structure of our data (see Section 3) the estimation takes account of clustering of individuals in households.

As is common in the SEM literature we rely on a number of diagnostic statistics to determine the adequacy of model fit. Firstly, the root mean square error of approximation (RMSEA) which shows the amount of unexplained variance (Steiger and Lind, 1980). RMSEA ranges from 0 to 1 with smaller values indicating better fit. Secondly, the Comparative Fit Index (CFI) which considers the discrepancy between the data and the hypothesized model, while adjusting for sample size (Bentler, 1990). Thirdly, the Tucker-Lewis reliability index (TLI) which is an adjusted version of the normed fit index of discrepancy between the chi-squared value of the hypothesized model and the chi-squared value of the null model (Tucker and Lewis, 1973). Both CFI and TLI range from 0 to 1 with larger values indicating better model fit. Hu and Bentler (1999) suggest that acceptable model fit requires RMSEA < 0.06 and both CFI and TLI > 0.90. We also provide the Chi-square test of model fit for the baseline model, which tests the null hypothesis that all slope parameters in the structural part of the model are 0 and the factor loadings in the measurement part of the model are all 1; for good model fit we would wish to reject this null[7]. In addition

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[5] As a consistency check, we also replicated estimates for the BHPS data (see below) using the gsem estimator in Stata v.13.

[6] Mplus uses a multi-step WLS method that analyses a matrix of polychoric correlations rather than covariances; thresholds are estimated by ML and these are used to estimate a polychoric correlation matrix (Jöreskog, 1990).

[7] Standard SEM would normally report the Chi-square test for model fit, which tests for differences between the observed and expected covariance matrices. This test is not valid for the WLS estimator, because the distributional

to these formal tests model validity is also judged on the basis of the parameter estimates; specifically whether the estimates pass the 'sense test' in that they accord with expectations from theory and previous empirical findings. We also replicate the modelling with two different datasets as a further check on the robustness of our results.

4. Data

Our main data come from the first wave of the UK Household Longitudinal Study (Understanding Society); a nationally representative survey of approximately 40,000 households (University of Essex, 2012)[8]. Data are obtained from face-to-face interviews with all adults in each household and cover a number of topics including personal background, economic circumstances, family relationships, health and well-being, as well as expectations, aspirations and opinions on a variety of issues. Wave One interviews were carried out in 2009/10 and include a module on environmental attitudes and behaviours. Our analysis sample is restricted to people who commute to work on a regular basis in England[9]. We also restrict the sample to respondents who live in an urban area[10], have access to a car and who commute for up to 120 minutes each way by car or public transport. These latter restrictions ensure that it is reasonable to assume that the respondents have some choice over their commuting mode. The resulting sample size is n = 13,141; 6884 women and 6257 men (see Table 1). This is contrasted with the relatively small bespoke data sets used in previous HCM studies; for example Johansson et al. (2006) analyse 811 responses to a postal survey on mode choice for one specific route in Sweden and Yáñez et al. (2010) use data for 303 individuals working at University campuses in Santiago, Chile.

A number of advantages follow from our use of household survey data: firstly, larger sample sizes give us more statistical power to detect effects[11]; secondly, our results are generalisable to the population of

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assumptions are violated. In addition it is not appropriate for our large sample, as the probability of rejecting the null increases with sample size (Jöreskog, 1969).

[8] The data are available from the UK Data Service (http://ukdataservice.ac.uk/). Both the user and each data usage must be registered with the Data Service.

[9] It is necessary to restrict the sample to England because we cannot obtain comparable area level transport data (see below) for Scotland, Wales and Northern Ireland.

[10] The definition of 'urban' is based on the Office for National Statistics Classification of Output Areas (www.ons.gov.uk/ons/guide-method/geography/products/area-classifications/rural-urban-definition-and-la/index.html)

[11] This is particularly valuable for the factor analysis, resulting in more stable estimates (MacCallum et al., 1996).

commuters in England and not specific to a particular journey setting; thirdly, the data contains a rich set of individual and household characteristics for use as control variables. Finally, both the potential endogeneity between attitudes and choices, and the influence of focusing effects are minimised because Understanding Society is a general household survey, rather than one focused on commuting or the environment; the questions on mode choice and those on environmental attitudes and behaviours occur in separate sections of the survey with no apparent links between the two. Focusing effects mean that questions can elicit misleading responses; it is highly likely that when people are asked about their environmental attitudes and commuting choices in a survey designed to explore the link between the two, they will overstate the importance of the influence of the environment, and offer consistent answers in an effort to rationalise their behaviours. Further, individual's attitudes can be affected by their mode choices since they may modify their attitudes to reduce the cognitive dissonance arising from inconsistent attitudes and behaviours; attitudes can be altered ex post whereas behaviours cannot be. If this was the case then the latent construct for environmentalism would be endogenously determined, but this is unlikely in our data due to the nature of the household survey.

These advantages come with one shortcoming; while we have extremely rich information about individuals and households, we have only limited information about the journeys in question (for example we have time and mode but not monetary cost) and in particular we do not have information about the characteristics of the mode that is not chosen, so for example if someone chooses to commute by car we do not know how long that specific journey would take by public transport. Given that journey time and cost are key variables in any mode choice model, we overcome this by matching in area level data on local transport context in order to construct proxies for journey time and cost; specifically we include measures of the availability of local public transport and the amount of local traffic congestion (see below).

A list of all variables with definitions is provided in Appendix 1. Our choice outcome variable is usual commuting mode for the regular journey to work; a binary variable where 1 represents car and 0 represents public transport. We also have average one-way travel time for this journey, in minutes, which we include in some of our models. Our indicator variables (Y_s^q) are a set of responses to questions on

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environmental behaviours and attitudes. There are ten questions on behaviours, which ask things like: *do you leave the television on standby overnight?; do you wear extra clothes rather than turning the heating up?; do you buy recycled products?* The responses reflect frequency of engaging in that behaviour and most of the questions have a five point scale that ranges from 'never' to 'always'. There are also twelve questions on environmental attitudes. The majority of these ask whether the respondent agrees or disagrees with statements like: *climate change is beyond our control; it's not worth me doing things to help the environment if others do not do the same; any changes I make to help the environment need to fit in with my lifestyle.* Two of the attitudes questions have ordinal responses: *How would you best describe your current lifestyle?* has a five point scale, where 1 represents not really doing anything environmentally friendly and 5 represents being environmentally friendly in everything they do; *being green is an alternative lifestyle*, has a four point scale where 1 represents disagree strongly and 4 represents agree strongly.

In order to capture information on local transport context we use geographical identifiers available under Special License for the Understanding Society survey; these show the Local Authority[12] that each household is located in. We use these identifiers to match in information about local transport conditions provided by the Department for Transport. We derive two variables from the information available. The first is average traffic speed during rush hour, which is a proxy for the amount of traffic congestion in the local area. The second is the journey time to the nearest town centre by car relative to public transport; this is a proxy for the availability of public transport locally. We would expect the utility derived from choosing the car for commuting, relative to public transport, to be higher if there is less congestion and lower the better the availability of public transport. While we do not include monetary cost in our model due to a lack of available data, these relative journey time variables can be considered as proxy variables for the economic concept of opportunity cost, or cost in terms of time.

Other control variables include age (in years), household income, highest educational attainment, whether or not the household contains children (in various age groups), self-reported health and marital status. All estimation is carried out for men and women separately given the evidence from previous literature that

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[12] Local Authorities (LA) are a tier of UK local government; there were 353 LA in total in 2010, and 307 are represented in our analysis data. There are between 1 and 265 households in each LA in our sample (the mean is 43 and the median 33).

men and women differ in their commuting behaviour (Roberts et al., 2011) and their environmental beliefs (Anable et al., 2006).

Given the novelty of using household survey data to estimate a HCM, replication is an important step in the model validation process. All of our modelling is replicated using the British Household Panel Survey (BHPS). The BHPS was an annual longitudinal household panel that ran from 1991 to 2008 and had a very similar design to Understanding Society, with a similar set of interview questions, including, in 2008, a module on environmental attitudes and behaviours[13]. The main difference between the two data sets is that the BHPS is smaller; in total 13,454 face-to-face interviews were carried out in 2008, and our analysis sample (given the selection described above) is 830 women and 900 men.

5. Results

Descriptive statistics are presented in Table 2. 70% of the women in our sample commute by car, and 73% of men; men's average one-way journey time is slightly longer at 28 minutes compared to just under 24 minutes for women. Highest educational achievement is similar for both sexes, as is household income; household incomes are highly skewed and are used in log equivalised form in the models below. 70% of women are married or living as a couple compared to 76% of men. Average health for both men and women is 3.65 on a scale where 1 is poor and 5 is excellent. Average traffic speed on main roads during rush hour is just over 24 miles per hour, which is relatively slow and thus represents high levels of congestion[14]; the range is wide from 9.4 to 39.2 miles per hour. Public transport quality (measured as the time it takes to travel to the nearest town centre by car relative to public transport) suggests that it is on average three times faster by car, with a range between two and seven times faster; this reflects extremely variable public transport quality across the Local Authorities.

Men and women appear to be very similar in terms of their environmental behaviours; this may be because many of the behaviours are determined at the household level and the majority of our sample is living as a couple. The biggest difference is in taking own bags shopping, which women are more likely to

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[13] The BHPS cohort was incorporated into the Understanding Society survey from Wave Two (2010/11), but they are not part of our Wave One Understanding Society sample (www.esds.ac.uk/longitudinal/access/bhps/ukhls.asp)

[14] The maximum speed limit on most of these main roads is between 40 and 70 miles per hour.

do than men. Switching lights off in empty rooms is very common, as is taking own bags shopping, not leaving the television on standby overnight and separating rubbish for recycling[15]. In contrast not buying goods with excessive packing, having green energy or a green tariff and taking fewer flights where possible, are much less prevalent behaviours. There are more differences between the sexes in attitudes than behaviours. Women are more likely to think that the world is on course for environmental disaster. However, they are also more likely to think that the environmental crisis has been exaggerated, that it is not worth doing anything about climate change unless others do the same, and similarly that it is not worth the UK doing anything. It is not common for men and women to think they lead an environmental friendly life; the average score is around 2.6, on scale where 1 represents not really doing anything environmentally friendly and 5 represents being environmentally friendly in everything they do. The majority of men and women think climate change is beyond our control, and its effects are too far in the future to worry about. However, over 60% believe that climate change will affect the UK in the next 30 years. Generally environmental attitudes show a large degree of confusion and inconsistency, which accords with the findings of the review work carried out for the Department of Transport (Anable et al., 2006); it also contributes to the observed inconsistencies between attitudes and behaviour.

We have carried out both EFA and CFA on our 22 observed indicator variables to explore and verify the latent structure of the data. In the EFA the indicators are allowed to load freely, and the appropriate number of factors is chosen by looking at a number of different diagnostic statistics, including the eigenvalues for each factor[16], scree plots (Cattell, 1966) and chi-squared tests. For both men and women, all of these statistics suggest that two or three factors are superior to a one-factor model. In chi-squared tests the null hypothesis of one factor is rejected is favour of the alternative hypothesis of two factors, and a null of two factors is rejected in favour of three. Comparing the factor loadings in the two and three factor models, the two factor model has a 'cleaner' structure where both factors have very distinct loadings which can be justified on the basis of psychological theory, with all but one of the attitude

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[15] Separating rubbish for recycling is mandatory in some Local Authorities in England, but is voluntary in the vast majority of areas; it is facilitated by curb-side collections.

[16] The eigenvalue for a given factor reflects the variance in all the variables, which is accounted for by that factor. The Kaiser-Guttman criteria (Kaiser, 1960; Guttman, 1954) recommends retaining factors with an eigenvalue > 1.

indicators loading on the first factor and all the behaviour indicators loading on the second factor[17]. Thus, taking account of all this information, a two factor model is preferred.

Given that EFA suggests that it is reasonable to view our indicators for attitudes and behaviours as two separate constructs, CFA is then employed as the first step in the estimation of the measurement model in the SEM and here the indicators are forced to load onto their two respective factors. The results are shown in Table 3; the first two columns show the factor loadings for environmental behaviours and the last two for attitudes; in both cases the results are presented in descending order of the factor loadings for women. The factor loadings show how each indicator is associated with the underlying latent construct. For behaviours the indicators are normalised so that the loading on *not leaving the television on standby overnight* (TV) is set to unity. For women all other indicators have a higher loading than TV; *not buying goods with excess packaging* (packing) has the largest loading onto the behaviours factor, followed by *buying recycled products* (produce) and *taking fewer flights where possible* (flights), the lowest loadings are for *having green energy or tariff* (energy), *separating rubbish for recycling* (recycling). The ranking of loadings onto behaviour is very similar for men. For attitudes the loading on belief that they *lead an environmentally friendly life* (own life) is set to one to normalise the scale. For both women and men the largest loadings are for *it's not worth Britain trying to do anything about climate change* (Britain), *it's not worth doing anything unless others do the same* (others) and *the effects of climate change are too far in the future* (future), and the lowest loadings are for own life, *being green is an alternative lifestyle* (alternative) and *any changes I make have to fit in with my current lifestyle* (lifestyle).

The results for the latent variable model are presented in Table 4; these show the associations between the two latent constructs and observable individual characteristics. As is common in the SEM literature, standardised coefficients are reported for continuous variables, as these allow comparison of the relative size of the effects within models[18]. Non-standardised coefficients are reported for dichotomous and ordinal variables, and these show the estimated change in the dependent variable for a discrete unit change in the explanatory variable. For both men and women pro-environmental behaviours and

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[17] The attitude indicator that loads onto Factor 2, with behaviours, is the extent that respondents feel they are leading an environmentally friendly life. This could be seen as being closer to a measure of self-reported behaviour than any of the other attitude questions.

[18] In all cases the standardised coefficients are $\beta^* = \beta \left(\sigma_x / \sigma_q \right)$, where σ_x and σ_q are the standard deviations of the continuous explanatory variable x, and dependent variable q. Note that standardised coefficients should not be used to compare the relative size of the effects across different models.

attitudes are non-linearly related to age. Having children does not seem to matter for behaviours for men or women; but for both men and women it seems that having primary school age children means that it is less likely that you will have pro-environmental attitudes. Behaviours and attitudes are increasing in education for both men and women. Income has a negative association with pro-environmental behaviours for men and women, but it has a positive association with pro-environmental attitudes. Being married and having better health have a positive association with behaviours for both men and women, but have no effect on attitudes.

Table 5 shows the results for the mode choice model where the dependent variable is a dichotomous choice between commuting by car ($d_i = 1$) and by public transport ($d_i = 0$). Two pairs of models are presented; the second includes commuting time as an additional regressor; again standardised coefficient estimates are reported. In general the results are very similar whether or not commute time is included. In terms of the latent variables, having a latent tendency to pro-environmental behaviours in other areas of life has a negative effect on the probability of commuting by car. Similarly, latent pro-environmental attitudes have a negative effect on the probability of car commutes for men but no significant effect for women. In terms of the conditioning variables, there is a similar non-linear age effect for men and women. Having pre-school children means women are more likely to commute by car, but the effect is not significant for men. The probability of commuting by car is increasing in education for women but this is not significant for men. Household income has a negative effect for men. Married women are less likely to commute by car but married men are more likely to. Health has no effect; however it is worth stressing that this is a relatively healthy sample because by definition all respondents are working. The quality of public transport in the local area and the average traffic speed have the expected signs and are significant for both men and women; the better the public transport the less likely people are to commute by car and the higher the average traffic speed during rush hour (i.e the less congestion) the more likely.

The quantitative interpretation for the standardised coefficients in Table 5 is that, for any coefficient estimate $\hat{\beta}$, a one standard deviation change in the associated continuous explanatory variable results in $\hat{\beta}$ standard deviations change in the underlying latent dependent variable (the utility derived from choosing to commute by car). Hence, the standardised coefficients on the continuous latent explanatory

variables can be compared straightforwardly to those for other continuous variables. Here we see that for men the effects of environmental attitudes and behaviours are very similar in size to the effects of local public transport quality and average traffic speeds. For example, increasing pro-environmental attitudes by one standard deviation reduces the utility derived from car use by 0.109 standard deviations; this is almost identical to the increase in utility that arises from a one standard deviation increase in local traffic speeds. Similarly for women, having a latent tendency to undertaking environmental behaviours in other areas of life has a similar effect on reducing the utility from car use as having better local public transport, or more road congestion.

In the second pair of models where the respondents usual commute time is included, this has a negative effect as expected i.e. the longer your commute the less likely you are to use a car. Including commuting time means that household income is now significant and positive for women (it remains negative for men). This is unsurprising because, there is a close positive correlation between household income and commute time for men in particular; this correlation is due to the fact that the rational decision maker will choose to commute for longer only if they are compensated, and part of this compensation comes from the labour market in the form of higher wages[19]. However, it is also likely that commute time is endogenous in this model, not least because there is a two-way relationship between length of commute and mode, and also because there may be a set of unobserved factors which influence both mode and time[20]. Nevertheless the fact that inclusion of commute time does not substantively change our estimates of the relative importance of environmental behaviours and attitudes is a strong robustness check on our results.

Model fit statistics for the SEM are reported in the lower part of Table 5, and these are all supportive of our model specification. We can reject the null hypothesis of the chi-squared test that all slope parameters in the structural part of the model are 0, and the factor loadings in the measurement part of the model are all 1. The CFI are all above (or very close to) the recommended cut-off of 0.9; similarly the TLI are all very close to (but just below) 0.9. In addition the RMSEA for all four models are below 0.06.

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[19] Compensation for longer commutes can also come from the housing market in the form of better housing and/or neighbourhood characteristics (see Roberts et al, 2011).
[20] One such factor is 'trip-chaining', which arises where individuals make multiple stops on their commute, for example to take children to school or pick up shopping; this information is not available in our data.

For conciseness we do not report the results of estimating these models with our alternative data set (the BHPS) here. In summary the story is essentially the same; although the smaller sample sizes result in larger standard errors. The factor analysis suggests two latent factors, and both of these (environmental attitudes and behaviours) are significant in determining mode choice for both men and women; this is slightly different to the Understanding Society results, where only behaviours are significant for mode choice for women. As for Understanding Society, the BHPS estimates suggest that pro-environmental attitudes and behaviours reduce the probability of commuting by car; quantitatively these effects are larger in the BHPS data, and the effects of local public transport quality and congestion are smaller[21]. This replication is an important check on the robustness of our estimates.

6. Discussion

A number of important findings emerge from the estimation of our HCM for commuting mode choice. Firstly, we have shown that it is possible to use large secondary data sets for HCM estimation. This increases the generalizability and statistical reliability of our results compared to existing studies that rely on relatively small bespoke surveys, which are prone to selection problems and focusing effects, and include little information on individual characteristics with which to control for heterogeneity. Secondly, the factor analysis suggests that the indicator variables are representative of two latent constructs, environmental attitudes and behaviours. These attitudes and behaviours appear to be separable constructs and the latent variable model shows, for example, that while higher levels of education are associated with both more pro-environmental attitudes and behaviours, in contrast increased income has a positive association with attitudes but a negative one with behaviours. These results, in the context of the psychological ABC model of environmental decision making, suggest different antecedents for attitudes and behaviours. Behaviours are much more likely to be influenced by personal context and convenience than attitudes; this may explain the diverse income effects and also the fact that marital status and health are significant predictors of environmental behaviours but do not affect attitudes.

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[21] As our transport context information comes from area level data, caution is advised in interpreting the size of the public transport and congestion effects for the BHPS results because the number of individuals in each area in the BHPS is relatively small.

Thirdly, environmental attitudes and behaviours are significantly related to choice of commuting mode. For men, the more pro-environmental their attitudes and other lifestyle behaviours the less likely they are to use a car for the regular commuting journey. This result contrasts with the previous literature that has argued that attitudes will have little effect on high-constraint environmental behaviours like car-driving (Collins and Chambers, 2005). We cannot completely discount the possibility that mode choice behaviour is driving attitudes here; in that men who use public transport for their daily commute see themselves as environmental friendly and hence change their attitudes to align with this. However, the nature of our household survey data and the fact that the environmental questions are not directly related to commuting, or asked in the same survey module, reduce this possibility compared to the bespoke survey data that is normally used to estimate HCMs. For women other environmental behaviours are again significant, but in contrast attitudes have no significant effect. This may be because women's commuting choices are more constrained than men's, as evidenced by the fact that having pre-school age children significantly increases the probability that women will use a car for commutes but this is not significant for men. Previous literature has shown that women have more complex journeys to work than men, and are engaged in more trip-chaining resulting in non-direct home to work journeys (Hensher and Reyes, 2000).

Finally, our results are supportive of the ABC model of environmental decision making. Attitudes and behaviours influence the utility that an individual derives from different mode choices for the regular commute. Thus the commuting mode choice is an interactive product of 'internal' attitudes and 'external' contextual factors.

7. Conclusion

Persuading people to get out of their cars and to use alternative, more sustainable forms of travel is essential if governments are to achieve their ambitious climate change goals. However, in the UK, as in many other countries around the world, our attachment to the car persists. This paper has contributed to furthering our understanding of the way that people make travel choices; specifically what determines choice of mode for the regular commuting journey. Traditionally transport economics has focused on

time and cost, assuming these to be the main determinants of travel choices for the rational economic agent. HCMs have allowed us to integrate latent variables, reflecting underlying environmental attitudes and behaviours, into a model of mode choice; these variables are shown to be significant and their effects are similar in size to important contextual factors like the availability of public transport.

Integrating these latent variables into the mode choice model has facilitated a more sophisticated understanding of the decision making process. This is reflective of a more general acceptance of behavioural economics, which diverges from the narrow view of economic rationality, and incorporates psychological factors into models of individual decision making. Unusually, for applications of HCMs, we have used large nationally representative household survey data sets for model estimation; thereby increasing the generalizability and statistical reliability of our results.

The fact that psychological factors influence commuting mode choices can be exploited by policy makers who need to persuade us to make more environmentally friendly choices. Attempting to influence our attitudes towards the environment (for example via advertising campaigns or information provision) or our other environmental behaviours (for example by making recycling a convenient activity for households) are not substitutes for fiscal tools and regulation but they can be seen as part of a comprehensive policy toolbox, which is targeted at making our travel choices more sustainable. A similar toolbox has been used successfully in the UK, and other countries, to substantially reduce smoking behaviour (Bauld, 2011). As well as climate change, private car use also contributes to congestion, noise, poor air quality, road traffic accidents and low levels of physical activity; so there are many reasons to try and bring about a change in individual behaviours.

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Figure 1: Hybrid choice model (HCM) for commuting mode.
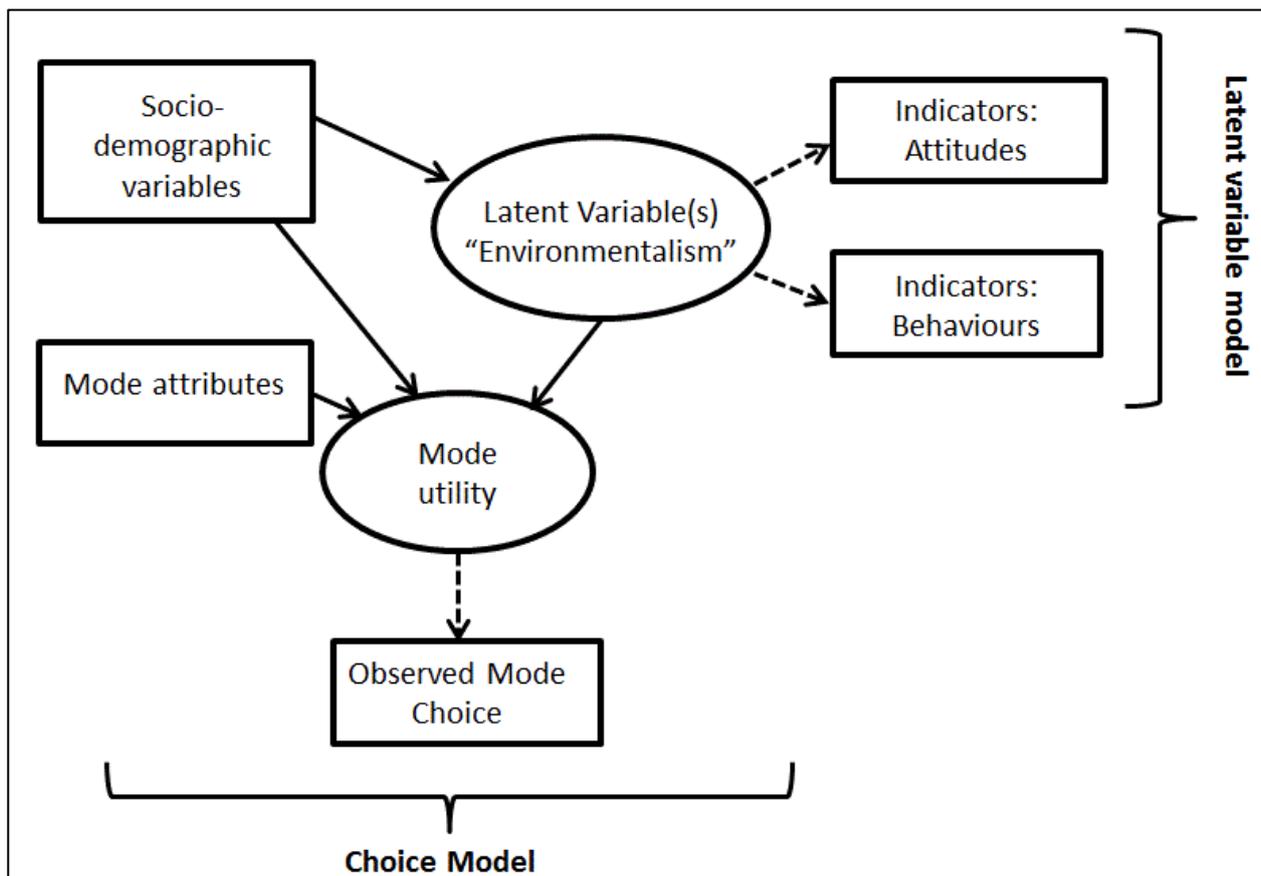
Notes: Adapted from (Ben-Akiva et al., 2002) We adopt the convention that observed variables are shown in rectangles, whereas those in ellipses are unobservable; solid arrows show cause and effect relationships, dashed arrows represent measurement equations.

Table 1: Construction of the analysis sample from Understanding Society Wave One

Inclusion and exclusion criteria		No of individuals
Total Adults interviewed in Understanding Society		50994
… with full face-to-face interviews*		47732
… who commute to work on a regular basis		22277
Do not live in an urban area	4364	
Have no access to a car	2620	
Commute for > 120 mins each way	54	
Do not commute by car or public transport	2075	
Missing values on key variables	23	
Analysis sample		**13141**
	Women	6884
	Men	6257

*Other interviews (by telephone and proxy) do not cover the full set of interview topics.

Table 2: Descriptive Statistics

Variable		Women			Men		
		mean	min	max	mean	min	max
Commute by car (not public transport)		0.70	0	1	0.73	0	1
Journey time (one-way in minutes)		23.88	1	120	28.27	1	120
Age (years)		40.67	16	83	41.07	16	81
Highest Education:	degree or above	0.45	0	1	0.43	0	1
	A level	0.20	0	1	0.21	0	1
	O level	0.28	0	1	0.25	0	1
Household Income (£ last month)		4207	116	20000	4332	35	20000
Children aged:	0-2	0.10	0	1	0.15	0	1
	3-4	0.08	0	1	0.10	0	1
	5-11	0.23	0	1	0.23	0	1
Married or couple		0.70	0	1	0.76	0	1
Health		3.65	1	5	3.65	1	5
Public transport quality		0.35	0.15	0.55	0.36	0.15	0.55
Average traffic speed (miles per hour, peak time)		24.53	9.4	39.2	24.12	9.4	39.2
Behaviours							
Not leave TV on standby overnight		3.61	1	5	3.56	1	5
Switches off lights in empty rooms		4.35	1	5	4.37	1	5
Not leave tap running when brushing teeth		3.26	1	5	3.25	1	5
Wears extra clothes rather than turn heating up		3.37	1	5	3.29	1	5
Does not buy goods with excess packaging		1.81	1	5	1.65	1	5
Has solar or wind energy or green tariff		1.18	1	3	1.18	1	3
Buys recycled products		2.54	1	5	2.45	1	5
Takes own bags shopping		3.75	1	5	3.15	1	5
Separates rubbish for recycling		3.61	1	4	3.60	1	4
Takes fewer flights where possible		1.90	1	5	1.89	1	5
Attitudes							
Leads an environmentally friendly life		2.62	1	5	2.54	1	5
Being green is 'alternative lifestyle'		2.55	1	4	2.48	1	4
Own behaviour contributes to climate change		0.54	0	1	0.49	0	1
Prepared to pay more for env. friendly product		0.43	0	1	0.40	0	1
World on course for major env. disaster		0.52	0	1	0.46	0	1
Environmental crisis has been exaggerated		0.54	0	1	0.45	0	1
Climate change (CC) is beyond our control		0.70	0	1	0.65	0	1
Effects of CC are too far in the future		0.68	0	1	0.62	0	1
Changes made have to fit in with current lifestyle		0.31	0	1	0.33	0	1
Not worth doing anything unless others do same		0.66	0	1	0.56	0	1
Not worth UK trying to do anything		0.67	0	1	0.58	0	1
CC will affect UK in next 30 years		0.64	0	1	0.61	0	1

Table 3: Confirmatory Factor Analysis: Factor Loadings

	Environmental Behaviours			Environmental Attitudes	
	Women	Men		Women	Men
Packing	2.756	2.075	Britain	4.543	4.555
Produce	2.524	2.103	Others	4.397	4.260
Flights	2.320	1.616	Future	4.383	4.403
Bags	1.971	1.916	Control	4.074	3.880
Heating	1.756	1.160	Exaggerate	3.835	3.855
Tap	1.726	1.451	30 years	3.814	4.012
Lights	1.528	1.109	Disaster	3.612	3.731
Energy	1.389	1.166	Pay More	2.854	3.163
Recycle	1.300	0.880	Own Resp	2.787	2.994
TV$^\$$	1.000	1.000	Lifestyle	2.547	2.764
			Alternative	1.447	1.407
			Own Life$^\$$	1.000	1.000
n	6884	6257		6884	6257

Notes: all estimates are significant at p<0.0001. $^\$$denotes loading fixed at unity via normalisation.

Table 4: Latent Variable Model Results

Latent dependent variable		Environmental Behaviours		Environmental Attitudes	
		Women	Men	Women	Men
Age		0.672***	0.512***	0.248***	0.293***
Age sq		-0.383***	-0.274**	-0.239***	-0.232***
Children aged	0-2	-0.039	0.081*	-0.066	0.027
	3-4	0.052	-0.013	-0.078	0.028
	5-11	0.003	-0.016	-0.110***	-0.075**
	12-15	-0.016	0.003	-0.032	-0.023
Educ	Deg	0.556***	0.566***	0.616***	0.629***
	Alev	0.243***	0.286***	0.435***	0.478***
	Olev	0.098*	0.084	0.279***	0.337***
Household Income		-0.031**	-0.057***	0.097***	0.099***
Married		0.143***	0.230***	0.016	0.051
Health Status		0.040***	0.065***	-0.005	-0.0041
n		6884	6257	6884	6257

Notes: Standardised coefficients ($\beta^*= \beta (\sigma_x/\sigma_q)$) reported for continuous variables and nonstandardized for dichotomous and ordinal variables. *, **, *** denote significance at p<0.10, p<0.05, p<0.001 respectively.

Table 5: Mode Choice Model Results

Dependent Variable: Car=1, Public Transport = 0		1a Women	1b Men	2a Women	2b Men
Environ. Behaviours		-0.173***	-0.183***	-0.169***	-0.182***
Environ. Attitudes		-0.004	-0.109***	0.001	-0.105***
Age		0.695***	0.635***	0.778***	0.700***
Age sq		-0.532***	-0.495***	-0.625***	-0.551***
Children	0-2	0.156***	0.070	0.152***	0.072
	3-4	0.185***	0.092	0.210***	0.094
	5-11	0.053	-0.071	0.013	-0.060
	12-15	0.037	0.019	0.009	-0.006
Education	deg	0.372***	-0.083	0.459***	-0.033
	Alev	0.370***	-0.067	0.409***	-0.036
	Olev	0.253***	-0.002	0.265***	0.018
Household Income		0.042	-0.112***	0.098***	-0.153***
Married		-0.164***	0.200***	-0.199***	0.195***
Health		-0.016	0.004	-0.012	0.007
Public transport quality		-0.157***	-0.180***	-0.126***	-0.160***
Average traffic speed		0.168***	0.106***	0.147***	0.100***
Commute time				-0.233***	-0.165***
n		6884	6257	6884	6257
SEM Diagnostic Statistics					
Chi-sq		62550.6***	51220.7***	62811.6***	51326.0***
CFI		0.899	0.908	0.900	0.909
TLI		0.887	0.897	0.889	0.898
RMSEA		0.042	0.038	0.041	0.037
C.I. for RMSEA		(.041, .043)	(.037, .039)	(.040, .042)	(.036, .038)

Notes: Standardised coefficients ($\beta^* = \beta\ (\sigma_x / \sigma_y)$) reported for continuous variables and nonstandardized for dichotomous and ordinal variables. *, **, *** denote significance at $p<0.10$, $p<0.05$, $p<0.001$ respectively. Chi-Sq – Ho: all slope parameters in the structural part of the model are 0, and the factor loadings in the measurement part of the model are all 1. CFI - Comparative Fit Index. TLI - Tucker-Lewis reliability index. RMSEA - Root Mean Square Error of Approximation.

Appendix 1 : Variable Definitions.

Variable	Definition
Commute Mode Choice	Dichotomous, Car =1, Public Transport = 0
Commute Time	In minutes, one-way for regular commuting journey
Gender	Female = 1, male = 0
Age	In years
Education	Set of dichotomous variables for highest level of attainment: degree or higher, A level, O level; base category = no qualifications.
Household Income	Log annual equivalised household income in pounds sterling
Children	Set of dichotomous variables for whether there are any children in the household aged: 0 to 2, 3 to 4, 5 to 11, 12 to 15; base category = no school age or pre-school children.
Married	Dichotomous, Married or living as a couple = 1, single = 0
Health	Ordinal self-assessed health indicator; 1 poor, 2 fair, 3 good, 4 very good, 5 excellent.
Public transport quality	Public transport quality for each Local Authority. Travel time to nearest town centre, by car / by public transport. Source: Department for Transport Accessibility data for 2009 [Table ACS0408-2009].
Average traffic speed	Average vehicle speed (flow-weighted) during the weekday morning peak on locally managed 'A' roads for each Local Authority, miles per hour. Source: Department for Transport data on Journey Reliability [Table CGN0206a]. Mean of the monthly figures from 2009.
Indicators - Behaviours	
TV	does not leave TV on standby overnight. Frequency, 5 point scale.
Lights	switches off lights in empty rooms. Frequency, 5 point scale.
Tap	does not leave tap running when brushing teeth. Frequency, 5 point scale.
Heating	wears extra clothes rather than turn heating up. Frequency, 5 point scale.
Packing	does not buy goods with excess packaging. Frequency, 5 point scale.
Energy	has solar or wind energy or green tariff. Frequency, 3 point scale.
Produce	buys recycled products. Frequency, 5 point scale.
Bags	takes own bags shopping. Frequency, 5 point scale.
Recycle	separates rubbish for recycling. Frequency, 4 point scale.
Flights	takes fewer flights where possible. Frequency, 5 point scale.
Indicators - Attitudes	
Own Life	leads an environmentally friendly life. Extent of agreement, 5 point scale.
Alternative	being green is 'alternative lifestyle'. Extent of agreement, 4 point scale.
Own Resp	own behaviour contributes to climate change (CC). Agree/Disagree.
Pay More	prepared to pay more for environ. friendly products. Agree/Disagree.
Disaster	world on course for major environmental disaster. Agree/Disagree.
Exaggerate	the environmental crisis has been exaggerated. Agree/Disagree.
Control	CC is beyond our control. Agree/Disagree.
Future	the effects of CC are too far in the future. Agree/Disagree.
Lifestyle	changes made have to fit in with current lifestyle. Agree/Disagree.
Others	not worth doing anything unless others do the same. Agree/Disagree.
Britain	not worth UK trying to do anything about CC. Agree/Disagree.
30 years	CC will affect UK in next 30 years. Agree/Disagree.

Source: Unless otherwise stated variables are obtained from Understanding Society, Wave One.