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UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL, HUMAN AND MATHEMATICAL SCIENCES

School of Social Sciences

Division of Social Statistics

Investigating Pro-Environmental Behaviours using a Multilevel Modelling Approach

by

Hiu-Tung-Vivian So

Thesis for the degree of Doctor of Philosophy

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UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF SOCIAL, HUMAN AND MATHEMATICAL SCIENCES

Social Statistics

Thesis for the degree of Doctor of Philosophy

INVESTIGATING PRO-ENVIRONMENTAL BEHAVIOURS USING A MULTILEVEL MODELLING APPROACH

Hiu-Tung-Vivian So

This thesis investigates the roles of individual, household and country in individuals' proenvironmental behaviours and aims to understand the relationship between environmental attitudes and behaviours using a multilevel modelling approach.

The first and second papers analyse factors influencing individuals' environmental behaviours in the United Kingdom using data from Wave 4 of the Understanding Society, UK Household Longitudinal Study. General environmental behaviour, as well as home-, transport- and purchasing-related behaviours are studied. The main focus is to highlight the role of the household on these individual behaviours. To account for the complex hierarchical structure of the survey data, where households are clustered within interviewers and geographical areas, both studies propose, for the first time, a cross-classified multilevel modelling approach. Results show that household, interviewer and area have significant effects on the reported environmental behaviours. The findings also suggest that individuals' personal and environmental values have significant impacts on their behaviours.

The third paper examines cross-national differences in individuals' environmental behaviours by exploring how individual- and country-level factors influence their behaviours and how the relationship between personal environmental attitudes and behaviours varies across countries using a multilevel modelling approach. Analysis is conducted on the 2010 Environmental module of the International Social Survey Programme, a cross-national survey that deals with environmental behaviours and attitudes. General environmental behaviour, as well as home-, purchasing-, transport- and recycling-related behaviours are considered. Results show that both individual- and national-level variables have substantial effects in explaining different types of environmental behaviours. The inclusion of the random slope on environmental attitude also provides evidence that the effects of individuals' environmental attitudes on their environmental behaviours vary significantly across nations.

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Academic Thesis: Declaration Of Authorship

I,	Hiu-Tung-Vivian So declare that this thesis and the work
pre	sented in it are my own and has been generated by me as the result of my own original
res	earch.
'In	vestigating Pro-Environmental Behaviours using a Multilevel Modelling Approach'
I co	onfirm that:
1.	This work was done wholly or mainly while in candidature for a research degree at this
	University;
2.	Where any part of this thesis has previously been submitted for a degree or any other
	qualification at this University or any other institution, this has been clearly stated;
3.	Where I have consulted the published work of others, this is always clearly attributed;
4.	Where I have quoted from the work of others, the source is always given. With the
	exception of such quotations, this thesis is entirely my own work;
5.	I have acknowledged all main sources of help;
6.	Where the thesis is based on work done by myself jointly with others, I have made clear
	exactly what was done by others and what I have contributed myself;
7.	None of this work has been published before submission.
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Dat	re:

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Abbreviations

Akaike Information Criterion (AIC) British Household Panel Survey (BHPS) Corruption Perceptions Index (CPI) Confidence Interval (CI) Confirmatory Factor Analysis (CFA) Deviance Information Criterion (DIC) Effective Sample Size (ESS) Ethnic Minority Boost Sample (EMBS) Exploratory Factor Analysis (EFA) General Population Sample (GPS) Greenhouse Gas (GHG) Human Development Index (HDI) International Social Survey Programme (ISSP) Iterative Generalised Least Squares (IGLS) Marginal Quasi-likelihood (MQL) Markov Chain Monte Carlo (MCMC) Norm-Activation Model (NAM) Penalised Quasi-likelihood (PQL) Primary Sampling Unit (PSU) Structural Equation Modelling (SEM) Theory of Planned Behaviour (TPB) UK Household Longitudinal Study (UKHLS) Variance Partitioning Coefficient (VPC) Value-Belief-Norm Theory (VBN)

Chapter 1: Introduction

1.1 Research Purpose

Over the last few decades, the study of environmental behaviours has emerged in a variety of research disciplines. Psychologists are interested in examining the psychological factors that influence people's environmentally friendly behaviours; urban planners are particularly interested in how sociodemographic characteristics play an important role in travel-related environmental behaviours; policy makers on the other hand are interested in understanding how and why people engage in different pro-environmental behaviours for better policy making. It is hoped that changing environmental behaviours will lead to positive effects on the environment, in particular in terms of a reduction in greenhouse gas emissions. Hence, a better understanding of environmental behaviours is crucial. Therefore, the main research aims of this thesis are to investigate the individual, household and country effects in individuals' pro-environmental behaviours and to understand the relationship between environmental attitudes and behaviours in the United Kingdom and across the world. The study uses a multilevel modelling approach.

1.2 Outline of the Thesis

The thesis starts with an Introduction chapter which presents the overall aims and research questions of the whole study and outlines the objectives of the three working papers. It also discusses relevant literature on pro-environmental behaviours and theoretical frameworks, the concepts of interviewer effects in the context of on measurement errors and multilevel modelling for both continuous and ordinal outcomes. Three papers are then presented. Paper 1 and Paper 2 focus on pro-environmental behaviours in the United Kingdom while Paper 3 expands the scope to investigate pro-environmental behaviours cross-nationally. Each paper consists of five main sections: Introduction, Data, Methodology, Results and Discussions, as well as a Conclusion. Finally, the thesis ends with a Conclusion chapter which summarises the findings and conclusions from all three papers.

1.3 Aims of the Study

Human behaviours indirectly cause global climate change problems through the emission of greenhouse gas (GHG). According to Department of Business, Energy and Industrial Strategy (2017), a total of 495.7 million tonnes GHG was emitted in the United Kingdom (UK) in 2015. The UK government has been monitoring the GHG emissions and its impacts on climate

change over the last few decades. Statistics has shown that emissions have decreased substantially since the early 2010 (Department of Business, Energy and Industrial Stragtegy, 2017). Since the signing of the Kyoto Protocol in 1997, the UK government has been committed to reducing GHG emissions. It has been that one possibility to reduce GHG emissions is by promoting pro-environmental behaviours among the public (Dietz *et al.*, 2009; Fisher and Irvine, 2016). Therefore, it is important to understand the underlying factors of how people behave environmentally in order to inform effective policy making.

Most of the current research on environmental behaviours in the UK and other countries is restricted to investigating individual-level influences only. These studies aim to identify how different individual-level factors are important in explaining people's behaviours. However, as suggested by Lynn and Longhi (2011), attitudes and behaviours are very likely to be influenced by people who are living together and sharing a common household setting. Therefore, the role of the household should be taken into account when investigating individuals' behaviours.

Furthermore, existing research on pro-environmental behaviours is country specific and based on a single country sample (Oreg and Katz-Gerro, 2006). However, since GHG emissions and their consequences for the environment are not just relevant to a particular country, understanding how people behave in a cross-country comparison is crucial. It is important to know how and why people from different countries behave in order to encourage pro-environmental behaviours across the globe efficiently. As a result, there is an increasing need to investigate the role of various individual-, household- and country-level influences and variables on people's behaviours.

The first and second papers use the Wave 4 data from the UK Household Longitudinal Study (UKHLS) to examine individual's environmental behaviours in the UK. It is a national representative household survey conducted in the UK (covering England, Scotland, Wales and Northern Ireland). It measures a wide range of topics and contains questions related to individual's environmental behaviours and attitudes. The first paper focuses on general proenvironmental behaviours while the second paper expands the focus to three specific environmental behaviours. The sample data in the UKHLS are hierarchical in nature, with individuals nested with households. Due to the multistage sampling procedures, households are further clustered in primary sampling units (PSUs or geographical areas). As the survey is mainly conducted using face-to-face and telephone interviews, households are also clustered within interviewers. However, as a result of the allocation of cases among interviewers, interviewers are not completely nested within geographical areas (nor vice versa). Instead, interviewers and areas are cross-classified. In this case, individual- and household-level effects on individuals' behaviours are further complicated by interviewer and area effects. In

fact, survey literature has shown that survey response outcomes can be prone to interviewer effects. This study, therefore, is also interested in understanding how much reported individuals' differences in environmental behaviours are subjected to the influence of interviewers. However, there is a possibility that interviewer effects are confounded with the area effects and hence the analysis of interviewer effect becomes more complicated. In order to account for the cross-classified structure between the interviewers and areas, a cross-classified multilevel modelling approach is adopted to aim to separate possible confounding effects of interviewers. To summarise, the objective of these papers is to understand the role of household and to highlight the importance of individual's environmental attitude on different types of individual's environmental behaviours, as well as to identify the effects of interviewers and geographical areas on individuals' reported response outcome.

The third paper uses data from the 2010 International Social Survey Programme (ISSP) to examine how individual's environmental behaviours differ across countries. It is an annually run cross-national survey with more than 50 participating countries from all over the world. Similar to the UKHLS, it also collects information related to individual's environmental behaviours and attitudes. The paper focuses on the general environmental behaviour and four specific environmental behaviours. The sample data in the ISSP is also hierarchical in nature, with individuals clustered within countries. This paper uses multilevel modelling to identify how different individual- and country-level factors influence individual's behaviours and to examine how the relationship between individual's environmental attitudes and behaviours varies across countries.

1.4 Background: Pro-Environmental Behaviours

This section first defines pro-environmental behaviours, then describes the sociological frameworks that are commonly adopted in the literature and finally discusses the factors which have been found to be significant in explaining these behaviours.

1.4.1 Definition of Pro-Environmental Behaviours

Environmental behaviours are behaviours that have impacts on the environment, regardless of the degree or type of these impacts. Lindenberg and Steg (2007) define "all types of behaviours that change the availability of materials or energy from the environment or alter the structure and dynamics of ecosystems of the biosphere" as environmental behaviours. Under this definition, all behaviours that benefit or damage the environment or change the sustainability of the ecosystem are considered as environmental behaviours. The impacts of these behaviours can be either positive or negative, and such behaviours can either directly or indirectly create an impact on the environment. Stern (2000) defines the behaviours that

have a positive impact on the ecosystem as *impact-oriented* pro-environmental behaviours (or sometimes referred to environmentally significant behaviours), regardless of whether people are aware of the impacts they may or may not have made. Steg and Vlek (2009) expand the scope of pro-environmental behaviours under this definition to include behaviours that are able to minimise the harm on the environment instead of limiting them to those having positive impacts. Meanwhile, pro-environmental behaviours can also be defined as behaviours that are intentionally acted to reduce the negative impacts on the physical world. Under this definition, there is a strong emphasis on actions that one performs consciously to benefit the environment. Stern (2000) defines this type of behaviours as intent-oriented because this definition highlights the intention to benefit the environment. The main difference between the impact-oriented and intent-oriented definitions is that the latter one stresses on the conscious decision (or intention) of being environmentally friendly while under the definition of impact-oriented behaviours people are believed to act environmentally friendly without any intention to benefit the ecosystem. Nevertheless, proenvironmental behaviours receive research attentions from many disciplines. Both definitions manage to narrow the term "environmental behaviours" and further help the researchers to focus on the behaviours being studied. In this study, "environmental behaviours" are defined as any behaviour, regardless of intention or not, that can benefit the ecosystem or minimise the harms on the environment.

Pro-environmental behaviours have been widely studied by researchers to understand the underlying determinants of these behaviours. These studies mainly focus on how external (such as neighbourhood settings and institutional structures) and psychological (or internal, such as attitudes and personal values) factors affect an individual to act pro-environmentally. Some studies narrow the focus to specific behaviours while some researchers have tried to examine the overall pro-environmental performance. Swami et al. (2011) and Barr (2007) focus on household waste management behaviours, such as household recycling behaviours. Meanwhile, Heinonen and Junnila (2014) and Sapci and Considine (2014) attempt to identify the factors that explain household energy consumption. Apart from studying the behaviours at household level, researchers are also interested in various individuals' behaviours, such as personal transport use (e.g., Anable, 2005; Thøgersen, 2006; Kahn and Morris, 2009) and environmental activism (e.g., Stern et al., 1999; Fielding, McDonald and Louis, 2008; Dono, Webb and Richardson, 2010). These studies investigate different pro-environmental behaviours separately and such an approach is often referred to as a multidimensional approach. Since different behaviours are not necessarily correlated and behaviours may be motivated differently (Steg, van de Berg and de Groot, 2012), studying a specific type of proenvironmental behaviour is common in research. However, Kaiser and Wilson (2004) discuss the potential of using a unidimensional measure to capture how an individual behave

environmentally rather than looking at different dimensions of environmental behaviours separately. They compare a multidimensional Rasch measurement model with a unidimensional traditional Rasch measurement model. Their results show that although the multidimensional model has a better fit, the difference between the two models is practically insignificant. Longhi (2013) also uses a unidimensional measure by aggregating eleven proenvironmental behaviours from three domains into one measurement to capture the overall pro-environmental performance. This approach allows a wide variety of behaviours to be examined simultaneously and hence it is easier to distinguish the less environmentally friendly individuals from those who are more pro-environmental.

1.4.2 Frameworks and Sociological Theories in Understanding Pro-Environmental Behaviours

Many studies have applied established theoretical frameworks to understand the underlying determinants of pro-environmental behaviours and to predict individuals' behaviours. These frameworks are based on psychological theories and they provide well-established constructs and clear definitions for researchers to identify the psycho-social factors that drive one's pro-environmental behaviours (Bamberg and Möser, 2007). The Theory of Planned Behaviour (TPB; Ajzen, 1985; 1991) and the Norm-Activation Model (NAM; Schwartz, 1977) are the two most influential frameworks in environmental psychology research and have been widely applied in a wide range of studies related to pro-environmental behaviours. In addition to these well-established theories and models, the Value-Belief-Norm Theory of Environmentalism (VBN; Stern *et al.*, 1999; Stern, 2000) has been developed as an extension of the NAM.

The Theory of Planned Behaviour (TPB) has been applied in environmental psychology to explain pro-environmental behaviours. It is an extension of the Theory of Reasoned Action (Fishbein and Ajzen, 1975; Ajzen and Fishbein, 1980) which assumes individuals make rational choices. Individuals are believed to choose options with largest benefits against smallest costs. Under the TPB framework, reasoned decisions are directly or indirectly related to three components: attitudes, social norms and perceived behaviour control. Attitude is based on beliefs about the possible costs and benefits of behaviours and it reflects the degree to which the behaviours are positively or negatively evaluated; social norm is conceptualised as the perceived social pressure or expectation from others to perform an action and it reflects the extent to which an individual believes that the importance for others to approve or disapprove of his or her behaviours; and perceived behaviour control is the individual's perceived self-ability to perform the behaviours. According to this model, these three components determine behaviours via behavioural intention whereas perceived

behaviour control can also be used to predict behaviours directly. TPB has been successfully used to explain various types of environmental behaviours, including waste management (Kaiser and Gutscher, 2003; Mannetti, Pierro and Livi, 2004; Nigbur, Lyons and Uzzell, 2010), travel mode choice (Bamberg and Schmidt, 2003; Anable, 2005), environmental activism (Fielding, McDonald and Louis, 2008), environmental behaviours at workplace (Greaves, Zibarras and Stride, 2013) and general environmental behaviours (Whitmarsh and O'Neill, 2010; Niaura, 2013; de Leeuw *et al.*, 2015).

In contrast to the TPB which emphasises self-interest, both Norm Activation Model (NAM) and Value-Belief-Norm Theory on Environmentalism (VBN) are based on the altruism nature of human beings. The NAM assumes morality as the reason for individuals to engage in a particular pro-environmental behaviour because they feel such an action can benefit others. The central idea is that the moral obligation plays a key role for people to engage in pro-social behaviours. Under this framework, such moral obligations to action are referred to as personal norms. The NAM proposes that the personal norm is activated when someone is aware of the environmental problems, he or she feels responsible for the problems and recognises one's own behaviours can reduce the severity of the problems. Schwartz (1977) presumes that the personal norm is causally influenced by the level of awareness of the adverse problems, the perception that there are actions to relief the problem and the selfrecognition of own ability to perform such actions. Meanwhile, the VBN is an extension of the NAM (Stern et al., 1999; Stern, 2000). It proposes that problem awareness depends on personal values and ecological worldviews. Similar to the TPB, both NAM and VBN have also proven to be success in modelling different types of pro-environmental behaviours, such as travel mode choice (Eriksson, Garvill and Nordlund, 2006; Abrahamse et al., 2009; Lind et al., 2015), energy use and conservation (Steg, Dreijerink and Abrahamse, 2005; Abrahamse and Steg, 2009; Fornara et al., 2016), conservation of environment (Raymond, Brown and Robinson, 2011), general environmental behaviours (De Groot and Steg, 2009) and environmental citizenship (Stern et al., 1999).

1.4.3 Factors affecting Pro-Environmental Behaviours

Although the TPB, NAM and VBN have different propositions, they are mutually inclusive in identifying the key factors that may have impacts on pro-environmental behaviours (Steg and Vlek, 2009). Regardless of the frameworks applied in the previous research, most of these studies are always keen on examining environmental behaviours from two directions: 1) the importance of sociodemographic factors; and 2) the roles of socio-psychological factors (Dietz, Stern and Guagnano, 1998). In particular, socio-psychological factors can be further categorised as personal value and environmental value. Attitudinal factors influence

environmental behaviours and the link between them and the sociodemographic factors are complicated and interrelated. These factors are found to have different degrees of influences in explaining people's environmental behaviours (Dietz, Stern and Guagnano, 1998; Steg and Vlek, 2009). Dietz, Stern and Guagnano (1998) also suggest that contextual factors (or *situational factors*) should also be considered as they have an important role in affecting individual's values and behaviours. As argued by Lynn and Longhi (2011), people are influenced by those who share the same household setting. In cross-national research, the relationship between environmental attitude and behaviours is also moderated by these situational factors (Rhead, Elliot and Upham, 2015). As people are greatly influenced by their living settings and surrounding environments, these external factors are equally important as individual's sociodemographic and socio-psychological factors when we aim to explain people's complex environmental behaviours. The following section discusses how these three factors have impacts on individual's pro-environmental behaviours.

1.4.3.1 Sociodemographics and Environmental Behaviour

Many studies have investigated the relationships between environmental behaviours and sociodemographic factors. These sociodemographic variables can be treated as individual-and household-level. In many previous studies where only one individual from each household is interviewed, household-level variables are often treated as individual data in the analysis. Since we aim to separate the household's role from the role of individual factors, we treat information that belongs to an individual as individual-level and information that describe the household's characteristics as household-level. Regardless of which level the information belongs to, both individual- and household-levels sociodemographic variables are important in explaining environmental behaviours. In the following section, we review the exiting literature on individual- and household-level socio-demographic variables.

Individual-level Sociodemographics

Previous findings show that older people are more environmentally friendly behaved than younger people (Gilg, Barr and Ford, 2005; Barr, 2007; Swami *et al.*, 2011). Gifford and Nilsson (2014) suggest that cohort effect may be able to explain such a difference. The elderly may have experienced something in the past that the younger generations have not experienced. The wartime (1937 to 1945) and post-wartime (mid 1940s to early 1950s) periods are the time when there were limited resources that people have to conserve in their daily livings. This may explain why the older generation engages more in pro-environmental behaviours as they might have developed such behaviours in their early ages.

Recent studies have consistently shown that females are more likely to participate in environmentally responsible actions than males (Zelezny, Chua and Aldrich, 2000; Luchs and

Mooradian, 2012; Scannell and Gifford, 2013; Xiao and McCright, 2014). Luchs and Mooradian (2012) argue that the personalities of women explain such a gender difference. They suggest that women's personal characteristics tend to place more emphases on environmental concerns than men. Meanwhile, it is also suggested by Zelezny, Chua and Aldrich (2000)that females are more other-oriented and socially responsible that they tend to behave in a more pro-social way.

Education and income reflect social class to some extent. The argument that middle- to upper-middle-class individuals participate more in environmentally responsible behaviours is well supported by many studies. For instance, the study by Longhi (2013) on individuals' pro-environmental behaviours in the household context shows that education is strongly associated with behaviours. Kollmuss and Agyeman (2002) suggest that the more the education people received, the more knowledge about environmental issues and solutions to these problems they have. However, they also argue that education is not necessarily correlated with environmental behaviours. Nevertheless, it is still reasonable to assume education is an important determinant for behaving environmentally friendly. On the other hand, some environmental actions (such as installation of wall insulation) can be costly that poorer people may not be able to afford and, therefore, income is also significant in explaining pro-environmental behaviours (Gifford and Nilsson, 2014). Franzen and Meyer (2010) also argued that richer people are more likely to express environmental concerns than poorer people and hence the wealthier tend to behave more environmentally responsible. In contrast, Fairbrother (2012) shows that the poorer tend to be greener than the riches. Although there is an inconsistent literature, social status is an important factor that influences how people behave.

Differences in pro-environmental behaviours can also be explained by the cultural differences between ethnic groups or immigrants. Findings from Johnson, Bowker and Cordell (2004) and Ellis and Korzenny (2012) have demonstrated the significances of the contribution of ethnicity and immigrant status in the environmentally responsible actions.

Household-level Sociodemographics

As discussed by Lynn and Longhi (2011), people living together share the same household setting. Therefore, people can be encouraged to act environmentally friendly or hindered from behaving environmentally responsible by the same household factors.

Car access is a barrier that can hinder oneself from engaging in environmentally responsible behaviours, especially in the behaviours related to the choice of transport. Tanner (1999) shows that car ownership is strongly related to driving frequency and members from

households without car access prefer more environmentally friendly commuting methods, such as walking, cycling or using public transports.

Household structure and the presence of some particular groups of household members in the household also influence individuals' pro-environmental behaviours. A study of the UK household's energy consumption and carbon dioxide emission by Büchs and Schnepf (2013) demonstrates that household size and composition play an important role in residential carbon dioxide emission. The presence of children and pensioners in a household are also found to be significant in explaining individuals' environmentally friendly behaviours (Longhi, 2013). They can act as a barrier for the family members to behave environmentally as they put the vulnerable groups (pensioners and children) at a higher priority than the environment.

1.4.3.2 Personal Values and Environmental Behaviour

Personal values reflect the needs and desires of an individual and can be conceptualised as important goals that are responsible for shaping individual's motivation to act (Kollmuss and Agyeman, 2002; Poortinga, Steg and Vlek, 2004). Reflected by people's political orientation, left-right ideology, altruistic behaviours, religion belief, post-materialistic values, social and political trusts and personal values are significant determinants of pro-environmentally behaviours.

The majority of studies that investigate the relationship between political orientation and pro-environmental behaviours are conducted in the United States and Canada. It has been found that liberal supporters are more likely to behave environmentally friendly than the conservative supporters (Feinberg and Willer, 2013; McCright and Dunlap, 2013; McCright, Xiao and Dunlap, 2014). Moreover, Selman and Parker (1997) and Eilam and Trop (2012) suggest that when people are more involved in society-related issues, they are also more likely to behave environmentally. This can be supported by the findings from Raymond, Brown and Robinson (2011) and Scannell and Gifford (2013) that people would like to do something extra to protect the place where they are strongly attached to. Similar results also show that those who have higher attachment to their local areas tend to behave green (Scannell and Gifford, 2013; Anton and Lawrence, 2014).

Pro-environmental behaviours are pro-social, meaning that people want to benefit others and the society through engagement in voluntary works. People who are altruistic and willing to help others are found to be more environmentally concerned and behave in a more environmentally friendly manner (Stern, 2000; Thøgersen and Ölander, 2002; Milfont and Gouveia, 2006). Although Gifford and Nilsson (2014) suggest that the importance of religion in studying environmentally responsible actions is unclear, more recent findings have shown

that religions have a positive relationship with the pro-environmental behaviours. Some authors have demonstrated that Christian and Muslim beliefs that emphasise a responsible role in the Earth given by God are positively related to pro-environmental behaviours (Biel and Nilsson, 2005; Rice, 2006). Similar results have been found in a more recent study conducted by Hope and Jones (2014) on the relationship between religion and environmental attitudes and issues. Furthermore, Pepper, Jackson and Uzzell (2011) have also confirmed that religiousness is positively related to environmentally friendly behaviours.

Inglehart's theory on post-materialism (Inglehart, 1990;1995;1997) is commonly used to explain how the shifting of materialistic values to post-materialistic values influences how people behave. As suggested by Inglehart (1995), when people are satisfied with their basic survival needs (such as security and food), they begin to look for post-materialistic goals, such as personal self-development and well-being of other people. According to the theory, people start pursuing better and more sustainable living environment when they no longer need to spend time and resources to meet their basic material needs.

There is not much literature that study the influence of social and political trusts on environmental behaviours. Lubell (2002) examines the relationship between political trust and people's support on environmental protection. His finding confirms that a positive correlation exists. Meanwhile, a more recent study by Harring (2013) demonstrates a mixed finding from analysing an earlier wave of the ISSP. On the other hand, Fairbrother (2016) concludes that people who are trusting are more likely to support environmental protection than those who have lower trusts to their governments. Therefore, it is important to examine the role of trusts on environmental behaviours.

1.4.3.3 Environmental Values and Environmental Behaviour

Environmental value is often referred to as the general attitude towards the environment and it reflects a personal evaluation of the environmental issues and problems (Fransson and Gärling, 1999). The term "environmental value" can be used interchangeably with "environmental concern". Numerous studies have been conducted to investigate the association between environmental values and behaviours. Environmental concerns have been found to be positively associated to all types of pro-environmental behaviours to these actions (Kollmuss and Agyeman, 2002; Thøgersen and Ölander, 2006). An early study from Diamantopoulos et al. (2003), as well as a more recent study conducted by Pisano and Lubell (2017), also show that the explanation of environmental concerns and attitudes are stronger than sociodemographic factors.

Environmental values have different conceptualisation. They can be conceptualised as personal's views on different attributes related to the environment, such as environmental

attitudes, environmental knowledge, environmental problem awareness and responsibilities and environmental justices (Franzen and Meyer, 2010; Marquart-Pyatt, 2012a; 2015; Pisano and Lubell, 2017).

As discussed by Franzen and Vogl (2013), people react in three ways when they are exposed to environmental problems: to have rational insight into the problem, to be willing to act accordingly and to be emotionally affected by the consequences of environmental problems. The idea of having rational insight and willing to behave is in line with the central idea of the TPB framework (Ajzen, 1985;1991). Under this framework, individuals are assumed to make rational choices based on attitudes, social norms and perceived behaviour control. Attitude can be defined as 'the enduring positive and negative feeling about some persons, objects or issues' and it is closely related to the beliefs of a person on another person or an issue (Kollmuss and Agyeman, 2002). The meta-analysis studies conducted by Hines, Hungerford and Tomera (1987) and Bamberg and Möser (2007) demonstrate a consistent result for the importance of attitudes towards specific environmentally friendly behaviours. Moreover, in order for the individual to make rational choices, it is important for one to perceive his or her self-ability to act. Therefore, environmental knowledge plays an important role here. However, Kollmuss and Agyeman (2002) argue that the explaining power of environmental attitude is significant but could be relatively weak. They suggest that a positive attitude on environment can only directly influence low-cost environmentally responsible actions rather than more general or high-cost behaviours (Kollmuss and Agyeman, 2002). Nevertheless, environment attitudes play an important role in understanding people's sustainable actions and it should not be omitted when analysing behaviours.

Meanwhile, the concept of being emotionally affected by the problems come from the idea of NAM (Schwartz, 1977) and VBN (Stern *et al.*, 1999). According to these theories, an individual's personal norm activates when he or she is aware of an environmental problem or the negative consequences for not behaving green (Schwartz, 1977; Stern *et al.*, 1999; Stern, 2000). In this context, personal norm refers to the environmental responsibility which is defined as the individual's sense of obligation to take actions against environmental problems (Fransson and Gärling, 1999). The awareness of the problem is often referred to as *environmental awareness* and it can be defined as 'knowing the impact of human behaviours on the environment' (Kollmuss and Agyeman, 2002). When people are aware of the possible negative consequences of an environmental problem, they have a sense of obligation to behave appropriately in order to improve the situations so that others can be benefited from their behaviours. Meanwhile, people need to recognise their own abilities in order for them to act. Therefore, it is also important for an individual to have sufficient knowledge to notice and solve the environmental problems. The meta-analysis of Hines, Hungerford and Tomera

(1987) suggests that those who feel personal responsibility towards the environment are more likely to participate in pro-environmental behaviours than those who hold no such feeling of responsibilities. Furthermore, individuals may also anticipate personal threats when they are aware of the problem and hence they become more likely to engage in the relevant behaviours. Previous findings show that behaviours are correlated to high awareness of the problem consequences (Fransson and Gärling, 1999). In addition, the meta-analysis of Bamberg and Möser (2007) also shows a similar result.

In recent decades, there has been a heated debate on whether the richer countries should contribute more in solving environmental problems than the poorer countries (Çarkoğlu and Kentmen-Çin, 2015). This debate is rooted from the concept of environmental justice (Schlosberg, 2003). According to the United States Environmental Protection Agency (2017), environmental justice can be defined as 'the fair treatment and meaningful involvement of all people regardless of race, colour, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies'. This means that everyone in the world is entitled to equal environmental benefits. However, Schlosberg (2003) points out that developing countries are suffering from environmental problems which are primarily caused by other developed countries. There are studies that examine whether or not people from the developing countries are more reluctant to pay for the environment costs (Marquart-Pyatt, 2008; Çarkoğlu and Kentmen-Çin, 2015). Results show that people from low-income countries are less willing to make economic sacrifices to improve the environment. However, there are few studies which look into the relationship between people's view on environmental justice and personal environmental behaviours.

1.4.3.4 Contextual Factors and Environmental Behaviour

The differences in how people behave do not depend only on individual or personal factors but also on the external environments. A range of situational factors, such as accommodation characteristics, neighbourhood settings, physical environments and institutional structures, have an important role in explaining individual's environmental behaviours.

Household-level Contextual Factors

Individuals living in the same household share the same accommodation characteristics and neighbourhood setting. Hence, they are encouraged or restricted by the same household contextual factors. Accommodation characteristics are found to be important in explaining energy use in households. Energy performance in a dwelling has both direct and indirect impacts on energy use. Druckman and Jackson (2008) indicate that the dwelling types and the level of energy saving measures installed in the dwelling affect residential energy performance. Meanwhile, the level of energy saving measures varies with tenure types (Utley

and Shorrock, 2006). Therefore, it can be argued that both dwelling and tenure types have indirect impacts on the energy use in the household. According to Utley and Shorrock (2008), a detached dwelling has the highest amount of heat loss, followed by a semi-detached dwelling, terraced, bungalow and flat. Meanwhile, standard wall insulation is more common in registered social landlord housing than owner-occupied housing, local authority housing and private rented accommodation (Utley and Shorrock, 2006).

Another type of household-level contextual factor that influences individuals' behaviours is the neighbourhood setting. Gifford and Nilsson (2014) suggest that if people live near problematic sites, they are more aware of the environmental threats and hence more likely to participate in actions that can relief the environmental problems. People may also treat the poor environment situation as a threat and hence they become more responsive to behaviours that can have a good impact on the environment (Hartmann *et al.*, 2015).

Conflicting research findings have been found on whether residents from rural or urban areas behave more environmentally responsible. Berenguer, Corraliza and Martín (2005) show that rural residents are more likely to engage in pro-environmental behaviours than the urban residents. However, a more recent study by Ambrosius and Gilderbloom (2015) has a different conclusion that people living in the urban area are more environmentally friendly behaved than those living in the rural area.

Country-level Contextual Factors

Cross-national research has demonstrated that both environmental behaviours and concerns are strongly influenced by the country's economic and education development, demographics structure, societal values, political context and physical environmental conditions (Oreg and Katz-Gerro, 2006; Marquart-Pyatt, 2012a; Franzen and Vogl, 2013; Givens and Jorgenson, 2013; Çarkoğlu and Kentmen-Çin, 2015; Chaisty and Whitefield, 2015; Fairbrother, 2016; Pisano and Lubell, 2017).

From a cross-national perspective, Inglehart's theory on post-materialism (Inglehart, 1990;1995;1997) can also be used to explain individuals' differences across countries. Many studies show that people from developed countries behave greener than the poorer nations' citizens as they have higher post-materialistic values (Inglehart, 1995; Oreg and Katz-Gerro, 2006; Fairbrother, 2012). It is suggested that modernisation and economic development are the important reasons in explaining why citizens from the rich and the poor countries differ in their environmental behaviours. Furthermore, there are usually better infrastructures, facilities and education in developed countries which can encourage their citizens to behave more environmentally friendly (Dalton, 2005). Meanwhile, Fairbrother (2016) shows that there is a strong relationship between the trust and the support for environmental protection

within countries. Citizens from countries with higher trust in the society and government have a higher tendency to engage in green behaviour. According to the NAM (Schwartz, 1977) and the VBN (Stern *et al.*, 1999), behaviour is activated when an individual is aware of the consequences of environmental problems. Previous research shows that people who are living in degraded environments are more likely to have a higher awareness of the consequences and therefore they behave more appropriately (Kollmuss and Agyeman, 2002). It means that the quality of the country's physical environment has a direct effect on how their people behave.

1.4.3.5 Summary

Pro-environmental behaviours are complex. A range of factors are found to be influencing these behaviours directly or indirectly. Numerous studies have confirmed the importance of sociodemographics, personal values, environmental values and contextual factors (see Figure 1-1) in explaining individual's environmental behaviours. Depending on the survey design, data structure and analysis approach, these factors can be aggregated or disaggregated into different hierarchical levels: individual-, household- and country-level. In many previous studies, household-level variables are often treated as individual data. It is particularly true for non-household surveys where only one member of the household is interviewed.

Analysing disaggregated higher-level variables may lead to substantial statistical biases (Hox, 2010); more detailed information on the statistical issues will be reviewed in the later section.

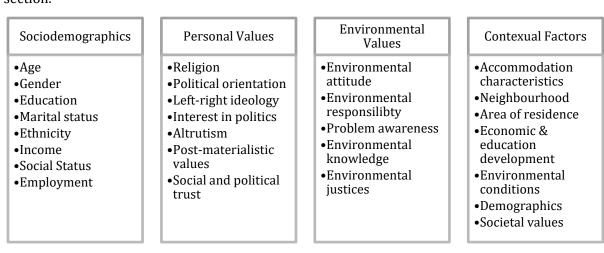


Figure 1-1 Factors Influencing Pro-Environmental Behaviours

1.4.4 Interviewer Effects on Survey Responses on Pro-Environmental Behaviours

Survey data are prone to a range of errors. The *total survey error* approach provides a comprehensive way to conceptualise and classify the errors. Biemer (2010) refers to the total survey error as the "accumulation of all errors that may arise in the design, collection,

processing, and analysis of survey data", meaning that errors can occur at any stage during the survey process. The total survey error consists of two error components: sampling error and nonsampling error (Biemer and Lyberg, 2003). Sampling error occurs when a sample is selected rather than choosing the whole population while nonsampling error includes all remaining errors that arise during the survey process (Biemer and Lyberg, 2003; Biemer, 2010). There are five main error sources that can contribute to the nonsampling error, namely, specification error, frame error, nonresponse error, measurement error and data processing error (see Figure 1-2).

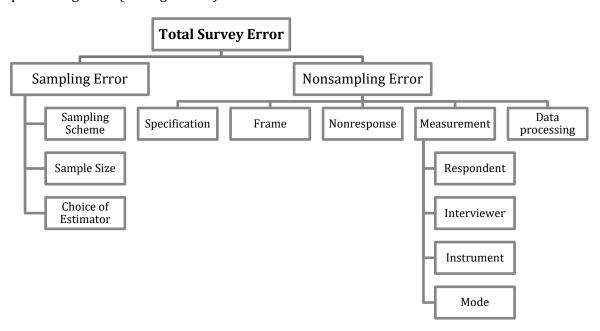


Figure 1-2 Composition of the Total Survey Error (Groves, 1989)

Nonsampling error, especially measurement error has been studied extensively in the survey literature. It has been suggested that measurement error is one of the most damaging error sources among all types of error (Biemer and Lyberg, 2003). Measurement error occurs when the answer from the respondent differs from the 'true' value. It can also be classified as an observation error (Groves, 1989). There are four components that can contribute to measurement error: respondent, interviewer, survey instrument and mode of survey (Figure 1-2; Groves, 1989; Biemer and Lyberg, 2003). In particular, interviewers have been shown to lead to substantial measurement errors on survey response outcome in interviewer-administered face-to-face and telephone surveys.

In interviewer-administered surveys, interviewers can contribute to the measurement errors in many ways; for example, the way they administer the questionnaires, their interactions with the respondents, their appearances, attitudes, characteristics and experiences may influence how the respondents respond to the survey (Groves, 1989; Hox, de Leeuw and Kreft, 1991; Biemer and Lyberg, 2003; Sturgis, 2015). The term *interviewer effect* can be used to describe this influence from the interviewers. Meanwhile, as noted by Biemer and Lyberg

(2003), this term has been used interchangeably with the *interviewer variance*, the *intra-interviewer correlation*, the *interviewer design effect* and the *correlated interviewer error*. Since interviewers tend to administer the survey and interact with the respondents in the same way over repeated interviews, the interviewer effect is systematic and it is also possible that there are some internal homogeneities in the respondents' response within interviewers (Biemer and Lyberg, 2003; Turner *et al.*, 2015). In other words, responses provided by those who are interviewed by the same interviewer are likely to be correlated. An early study shows that there is high intra-interviewer correlation in the response (O'Muircheartaigh and Campanelli, 1998). In a more recent study, Beullens and Loosveldt (2014) also demonstrate that interviewer effects occur in single survey items and in the relationships between survey items. Some researchers, however, argue that the similarities in response within interviewers may be due to the variation of nonresponse error across interviewers rather than the interviewer effect on survey responses (West and Olson, 2011).

A lot of studies have been attempted to explain interviewer effect and to understand the sources of such effect. Existing research on interviewer effects on survey response outcomes focuses on how the sociodemographic characteristics, attitudes, experiences and behaviours of interviewers (Davis and Scott, 1995; O'Muircheartaigh and Campanelli, 1998; Biemer and Lyberg, 2003; Bateman and Mawby, 2004), how the question types being asked in the surveys (Schnell and Kreuter, 2005; Tourangeau and Yan, 2007; Sakshaug, Yan and Tourangeau, 2010; Brunton-Smith, Sturgis and Williams, 2012) have an effect on respondents and how different types of respondents are affected by the interviewers (Weisberg, 2005). Although the findings are not very consistent, it has been found that interviewers' gender (Davis and Scott, 1995; O'Muircheartaigh and Campanelli, 1998; Gong and Aadland, 2010; Liu and Stainback, 2013), age (O'Muircheartaigh and Campanelli, 1998) and ethnicity (Loureiro and Lotade, 2005; Davis et al., 2010) are able to predict the intra-interviewer correlations. Moreover, more experienced and skilful interviewers are able to reduce the interviewer effect (Brunton-Smith, Sturgis and Williams, 2012; Turner et al., 2015). As discussed by Jann (2015), respondents are more likely to over-report in questions related to socially desirable behaviours (such as pro-social behaviours or voter turnout) during face-to-face interviews. On the other hand, people tend to under-report in socially undesirable or sensitive questions (Schnell and Kreuter, 2005; Tourangeau and Yan, 2007).

Pro-environmental behaviours are considered as pro-social or socially desirable behaviours. Therefore, in interviewer-administered survey, such as the UK Household Longitudinal Study that is used in the first and second papers of this thesis, the presence of interviewer effect on reporting pro-environmental behaviours may be non-negligible. Although there is not much research conducted on the interviewer effect on environmentally friendly behaviours, there

are a few studies investigating the relationship between interviewer effects and responses in environmental valuation surveys. Bateman and Mawby (2004) show that respondents tend to provide a more favourable answer to well-dressed interviewers when they are asked about their willingness to pay more for environmental goods. Meanwhile, respondents are also more likely to report their willingness to pay extra for recycling when they are interviewed by female or white interviewers (Gong and Aadland, 2010). In these two studies, respondents are asked about their preferences on pro-social behaviours. It is possible that respondents would have over-reported their behaviours, yet, both studies demonstrate that the interviewers' characteristics have some impacts on the respondents' answers.

From survey methodology perspective, interviewers do not only induce measurement error but also introduce other types of survey errors during different stages of the survey process. West and Blom (2017) point out that interviewers may be responsible for other non-sampling errors, such as coverage error, unit nonresponse error, item nonresponse and processing error. Since one of the aims of this thesis is to identify interviewer effects on individuals reported environmental behaviours, the following sections focus only on the interviewers' influence on respondents' survey response. Details on the estimation methods of interviewer effects are presented in the subsequent section.

1.5 Background: Review of Methodologies

1.5.1 Understanding Environmental Behaviours

Depending on the objectives of the study, different methodologies have been applied to understand the determinants of individuals' pro-environmental behaviours. In general, three types of statistical modelling are commonly used, namely structural equation modelling, linear regression modelling and multilevel modelling.

Structural equation modelling (SEM) is a popular statistical analysis method in understanding the relationships between environmentally responsible behaviours and the relevant explanatory variables. SEM is useful in identifying the latent variables and the constructs of behaviours. In particular, it is often used to examine the effect of the established psychological frameworks, such as the TPB, NAM and VBN. For instance, Fielding, McDonald and Louis (2008) apply SEM in their research to examine the effect of the TPB on individual's engagement in environmental activism whereas Lind *et al.* (2015) adopt a SEM approach to assess the variation explained by personal values and environmental beliefs in personal norms under the VBN framework. Furthermore, Barr (2007) uses path analysis to test a intention-behaviour relationship on household waste management behaviours in Exeter.

Meanwhile, Thøgersen and Ölander (2006) also apply SEM in their research to examine whether different environmental actions share common motivations.

Another common analysis technique is linear regression modelling. This simple modelling technique is adopted by Sapci and Considine (2014) to examine the association between household environmental attitudes and household energy use. Whitmarsh and O'Neill (2010) also apply such an approach to identify the role of pro-environmental self-identity in determining environmentally friendly behaviours. The study conducted by Longhi (2013) using Wave 1 of the UKHLS also use a linear regression model to identify the impacts of individual's and household's characteristics on individuals' pro-environmental behaviours. She applies separate regression models for different household types to identify the determinants for individuals' behaviours across different types of household. However, she does not take the hierarchical data structure into account.

The third approach, but much less commonly used in the literature in the context of environmental topics, is multilevel modelling. Tso and Guan (2014) adopt a multilevel modelling approach to account for area and household effects on residential energy consumption in the United States. Goulias and Kim (2001) also apply this approach to identify the roles of households and individuals in personal travel pattern and transport choice.

1.5.2 Multilevel Modelling

In social research, data are often clustered in nature. For example, students are nested within schools, patients are nested within hospital wards, cities are nested within countries, household members are nested within households and respondents are nested within interviewers. Depending on the nature of studies, variables can be defined at different levels (or groups). A standard statistical analysis approach, such as linear regression, relies on the assumption that individual observations in the sample are independent with each other. However, when the data are clustered, lower-level (or micro-level) units may not be necessary independent within a higher-level (or macro-level) unit. In educational research, students from the same school are taught by the same teacher may be influenced by the same teaching style; in survey research, respondents being interviewed by the same interviewer may be subjected to the same interviewer effect; and in household surveys, individuals from the same household have similar sociodemographic characteristics and share the same household setting. In this case, the independent assumption is no longer valid. Violating that assumption can lead to a strong downward bias in the estimates of standard errors and hence provides wrong statistical inferences (Hox, 2010). It is more problematic when individuals are highly clustered.

Traditionally, there are two analysis strategies for handling hierarchical data: aggregated and disaggregated approaches. Aggregation refers to the shifting of lower-level variables to a higher level while disaggregation means transferring the higher-level variables to a lower level. The most commonly used aggregated approach is the group-level analysis. It aggregates the micro-level data to macro level and fits a standard regression model to the aggregated data (Hox, 2010; Snijders and Bosker, 2012). In other words, the mean of the higher-level outcome variable is regressed on the means of the higher-level explanatory variables. However, there are potential problems with this analysis strategy. Firstly, information is lost during aggregation and hence the statistical analysis power is reduced (Hox, 2010). Secondly, there is a shift of meaning in the interpretation of the results (Snijders and Bosker, 2012). During aggregation, the lower-level units are shifted to higher level and hence these variables become higher-level variables rather than containing information at the original lower level. Thirdly, making conclusion at the lower level based on the analyse of higher-level data is misleading (Hox, 2010). Since the aggregated data do not provide any information about the lower-level units (Snijders and Bosker, 2012), the correlations between higher-level variables cannot be used to formulate conclusion about the lower-level variables. This is well-known as the ecological fallacy (Robinson, 1950) and has been discussed and documented in many previous literature (for example, Alker, 1969; Steel and Holt, 1996; Subramanian et al., 2009). The last potential problem of aggregating the lower level is that it does not allow potential cross-level interaction effects (Snijders and Bosker, 2012). Since all the lower-level units become the higher level, it is not possible to examine the cross-level interaction effects as all units are at the same level.

In contrast to the group-level analysis which involves aggregation, contextual analysis is a disaggregated strategy. In contextual analysis, higher-level explanatory variables are included in the standard regression model when the data are analysed at the lower level (Hox, 2010; Snijders and Bosker, 2012). This approach assumes all higher-level variances can be explained by the higher-level explanatory variables, yet, this assumption may not hold (Hox, 2010). Therefore, incorrect standard errors are produced for the higher-level variables as the clustering nature of the data is ignored. Moreover, making conclusion at a higher level based on analysing the lower-level unit is also misleading (Hox, 2010). Another disaggregated approach for handling hierarchical data is the fixed effect model (or the *analysis of covariance*). It involves the inclusion of dummy variables for each and every higher-level groups (Snijders and Bosker, 2012). This method is problematic especially when the number of clusters is very large and when the aims of the study is to investigate between-group and within-group differences. Snijders and Bosker (2012) suggest that such a method would lead to severe type I errors for between-group and within-group differences. Meanwhile, the generalised estimating equation (GEE; Liang and Zeger, 1986; Zeger and Liang, 1986)

approach is also a commonly used disaggregated approach to analyse hierarchical data. It fits a single-level model on the clustered data with the standard errors being adjusted for the clustering to take the within-group correlation into consideration (Goldstein, 2011). It is also referred to as a marginal (population-average) model (Hardin and Hilbe, 2013). This method assumes a generalised linear model for the expected values of the outcome variable and conditional on the predictor variables without assuming any variance or covariance structure (Snijders and Bosker, 2012; Hardin and Hilbe, 2013). Although the GEE approach is able to address different types of research questions, it treats clusters as a nuisance rather than a focal interest (Goldstein, 2011). Therefore, if the central interest of the research is the between-group variability, the GEE approach would not be appropriate as it is unable to estimate the between-group variances.

Clustering or the hierarchical structure of the data can be a phenomenon that researchers are interested in. Unlike the aggregated and disaggregated methods which have previously discussed, multilevel analysis is a method that is specifically designed for analysing hierarchical data. Multilevel modelling is also known as 'random coefficient modelling', 'variance component modelling' and 'hierarchical linear modelling' (Hox, 2010; Snijders and Bosker, 2012). It is a disaggregated approach which includes nested random coefficients (random error terms) in a standard regression model to account for the clustering or dependency. The extension is to allow an error term at each level to adjust the corresponding standard errors. Moreover, it allows within-group and between-group relations to be studied within one analysis. Hence, all the levels can be analysed simultaneously (Snijders and Bosker, 2012). Multilevel analysis is based on the concepts of contextual modelling and mixed effects modelling. As in contextual analysis, multilevel modelling treats the individual and the group as distinct sources of variability. Therefore, it allows the variation of the outcome variable to be partitioned into between-group and within-group components. Unlike the fixed effects model which requires many parameters to estimate the group effects, a multilevel model requires much fewer parameters.

Since the basis of multilevel modelling was established in the late 1980s, multilevel analysis has been widely applied in educational research (Goldstein *et al.*, 1993; Gray *et al.*, 1995) and it has become more popular in sociology, psychology, criminology, demography, survey methodology and other types of social science research. Due to advanced programming technologies and the Bayesian algorithms, more flexible model specifications for more complex structures that are based on multilevel model have been developed (Goldstein, 2011). These models can deal with more complicated hierarchical structures, such as the cross-classified structure where levels are not nested in each other but a lower-level unit

belongs to more than one higher-level unit. Furthermore, these models can also deal with non-continuous outcomes and allow nonlinear models to be estimated.

1.5.2.1 Multilevel Model for a Continuous Outcome

The focus of the first paper and part of the third paper is on multilevel models with a continuous outcome. The general form of a two-level random intercept model for purely hierarchical data is as follows:

$$y_{ij} = \beta_0 + \boldsymbol{\beta}_1^{\mathrm{T}} \mathbf{X}_{ij} + u_j + e_{ij}$$
 Equation 1-1

where y_{ij} is the continuous outcome variable for individual i from the j^{th} group. \mathbf{X}_{ij} is a vector that contains the explanatory variables which can be defined at the individual-level or group-level. These predictor variables also include same-level and cross-level interaction effects. β_0 is the overall intercept in the linear relationship between the dependent variable and the independent variables specified in the model whereas $\boldsymbol{\beta}_1$ is a vector of coefficients for the predictor variables \mathbf{X}_{ij} in the model. The parameters e_{ij} and u_j are the random effects for the first level (individual-level i) and second level (higher-level group j). These random effects are assumed to follow a normal distribution with mean zero and variances σ_e^2 (individual-level) and σ_u^2 (higher-level), and to be mutually independent. σ_e^2 and σ_u^2 are referred to as between-individual and between-group variances respectively. On average, groups with a larger value of u_j are more likely to have higher outcome values while a smaller value of u_j tend to have lower responses.

Equation 1-1 represents a random intercept model (or hierarchical linear model). The first part of the model (i.e., $\beta_0 + \beta_1^T \mathbf{X}_{ij}$) is called the fixed part as these coefficients are nonstochastic, and the remaining part of the model (i.e., $u_j + e_{ij}$) is considered as the random part. In a random intercept model, group differences vary along the intercept of the average group or the fixed intercept β_0 . It also assumes that the relationship between y_{ij} and \mathbf{X}_{ij} is the same in all groups. The random part of the model can be further extended by allowing the outcome and predictor variables relationship to vary randomly across groups, resulting in a random slope model. Meanwhile, the random part of the model can also be extended to handle non-purely hierarchical data, for example cross-classified or multiple membership structures.

Since the random part of the model (i.e., e_{ij} and u_j) are the error terms at the individual- and group-level that are left unexplained by the explanatory variables \mathbf{X}_{ij} , they contain variability of the outcome variable y_{ij} that are not explained by the model. The total variation of y_{ij} can be partitioned into the sum of level-one and level-two variances while the covariance between two level-one units in the same group is the level-two variance. Therefore, the

Variance Partitioning Coefficient (VPC) can be calculated as the ratio of the covariance between two individuals from the same group and the total variance in a random intercept model. The VPC is a measurement of the proportion of total variance contributed to the group level. In a two-level random intercept multilevel model, VPC can also be interpreted as the intra-unit correlation between two randomly selected individuals in a specific group.

1.5.2.2 Multilevel Model for an Ordinal Outcome

The focus of the second paper and part of the third paper is on multilevel models with an ordinal outcome. For a C-category ordinal response y_{ij} of individual i from the j^{th} group, the general form of the random intercept cumulative logit model for two-level hierarchical data is as follows:

$$\log \left[\frac{\Pr(y_{ij} \le c)}{\Pr(y_{ij} > c)} \right] = \operatorname{logit}(\gamma_{cij}) = \alpha_c - (\boldsymbol{\beta}^{\mathsf{T}} \mathbf{X}_{ij} + u_j), \quad c=1, 2, \dots, C-1$$
 Equation 1-2

where $\Pr(y_{ij} \leq c)$ is the cumulative probability that the response y_{ij} takes on a value up to the c^{th} category for individual i from the j^{th} group. The vector \mathbf{X}_{ij} contains explanatory variables which can be defined at both individual- and group-levels. The explanatory variables are not limited to a single-level, but also include same-level and cross-level interactions. Meanwhile, $\mathbf{\beta}$ is a vector of parameter coefficient for each of the independent variables in the model, and it presents the effect of a one-unit change in the covariate on the log-odds of being in a lower category of y_{ij} rather than a higher category after adjusting for the group effect u_j and keeping all other covariates constant. It is also known as the cluster-specific effect of the explanatory variables. Furthermore, α_c is the threshold parameter which can be interpreted as the log-odds that an individual i with $\mathbf{X}_{ij}=0$ and $u_j=0$ has a response of c or lower. It is also the overall intercept in the linear relationship between the log-odds that y_{ij} takes on a value up to category c and the explanatory variables. Since the logits of the cumulative probability are modelled, the threshold values are ordered with $\alpha_1 < \alpha_2 < \cdots < \alpha_{c-1}$. The term u_j is the random effect (or the group residual) of the group level and it is assumed to follow a normal distribution with zero mean and variance σ_u^2 .

Equation 1-2 represents a multilevel cumulative ordered logit model. In this model, the effects of the covariates on the cumulative odds are assumed to be constant for all categories on the logarithmic scale. This is known as the proportional odds assumption. Moreover, it is assumed that the random effect u_j is constant for all categories, i.e., u_j is independent of the category. However, this assumption of common cluster variance can be relaxed (Hedeker, 2008).

As in the random intercept model for continuous outcome which is presented in the last subsection, the VPC can also be calculated for the multilevel cumulative ordered logit model. There are multiple ways to calculate the VPC, including model linearisation, simulation, binary linear model and latent variable approaches (Goldstein, 2011). Among these approaches, the most commonly used method is the latent variable approach which is also referred to as the threshold specification of a logistic model. Unlike the multilevel model for a continuous outcome variable, the random intercept cumulative logit model includes only level-two residuals. This is because it is the probability of the individual taking value up to c^{th} category is being modelled rather than the value of a continuous outcome. For a logit model, the level-one random error term is unobserved and it is assumed to follow a standard logistic distribution with mean equals zero and variance equals to $\pi^2/3 \approx 3.29$ (Hedeker, 2008; Goldstein, 2011; Snijders and Bosker, 2012).

1.5.2.3 Methods for Estimating Multilevel Models

1.5.2.3.1 Maximum Likelihood Estimation

In multilevel modelling, parameter estimations can be carried out by various approaches. The most commonly used method is the maximum likelihood (ML) approach. It is a general estimation procedure for obtaining estimates for unknown parameters that maximise the likelihood of the observed data. Since the ML approach is generally robust (especially robust against mild violation of the normality assumption) and produces asymptotically efficient and consistent estimates (Hox, 2010), it is a popular method to estimate parameters in multilevel modelling. Goldstein (2011) also suggests that if there are several random coefficients in the model for estimations, the assumption of multivariate normality becomes flexible and the ML approach allows a convenient parameterisation for complex covariance structures at several levels. In general, ML estimates are obtained by maximising the likelihood function of the data. The *full maximum likelihood* (FML) and the *restricted maximum likelihood* (REML) are two commonly used likelihood-based methods.

Both FML and REML produce estimates with standard errors. Fixed and random components are included in the FML method, whereas only the variance component is included in the REML method (Hox, 2010). Although the estimates of the random parameters obtained from FML can be biased, Snijders and Bosker (2012) suggest that FML is still a more preferable approach as it allows deviance test for model comparison. Meanwhile, REML estimates have fewer biases since it takes account of the degree of freedom lost during the estimation of the random components (including variance and covariance parameters). Nevertheless, the FML and REML produce similar results (Hox, 2010).

An iterative algorithm is required for the computation of the ML estimates. The procedure starts with the generation of the starting values for various parameters of the fixed and random effects, follows by an iterative computation procedure to obtain new estimates for the fixed and random parts alternatively until the estimates converge. There are various algorithms, including *iterative generalised least squares* (IGLS) and *restricted IGLS* (RIGLS), to obtain the FML and REML estimates. Both algorithms are available in the MLwiN software which is specifically designed for analysing hierarchical data (Rasbash *et al.*, 2015).

1.5.2.3.2 Quasi-likelihood Estimation

In generalised multilevel models, quasi-likelihood estimation is applied to approximate the nonlinear link function by a Taylor series expansion. A Taylor series expansion can be used to approximate a nonlinear function by an infinite series of terms. When only the first term of the infinite series of terms is used, it is referred to as the first order Taylor approximation. Meanwhile, if the second term is also used, then it is the second order Taylor approximation. On the other hand, a Taylor series expansion also depends on the values of the parameters used for the linearization of the nonlinear function. The *marginal quasi-likelihood* (MQL) uses only the current estimated values for the fixed part of the multilevel model while the *penalised* (or *predictive*) *quasi-likelihood* (PQL) uses both fixed part and residuals. After applying the Taylor series expansion on the nonlinear part, the IGLS or the RILGS can be used on the resulting linear part to estimate the parameters of the multilevel model.

Literature has suggested that the second order approximation is more accurate than the first order while the PQL procedure produces better estimates than the MQL (Rodriguez and Goldman, 1995; Goldstein and Rasbash, 1996; Rodriguez and Goldman, 2001; Hox, 2010; Goldstein, 2011). Goldstein (2011) argues that the MQL procedure always underestimates the parameters. A simulation study conducted by Rodriguez and Goldman (1995) shows that even with a second order PQL, there are substantial downward biases in both fixed and random effects whenever there is a large random effect or small group size. The bias becomes more problematic when there are high intra-class correlations among small groups. An example of data with small group sizes and a high intra-class correlation is household data. There are usually less than five people living in a household and single households are also very common. There may also be nonresponse from some of the household members resulting in an average household size of less than two. Therefore, second order PQL estimates can still be biased. Moreover, the second order PQL estimation may also encounter convergence problem especially when the random effect is too small. In order to eliminate the potential biases or to avoid convergence problem, bootstrapping for at least five iterations based on the first order PQL estimates or shifting to Bayesian estimates are recommended (Rodriguez and Goldman, 2001). Since bootstrapping is very computational

intensive, using Bayesian estimation via Markov Chain Monte Carlo by using Gibbs sampling and Metropolis-Hastings sampling is a more preferable approach.

1.5.2.3.3 Markov Chain Monte Carlo Estimation

Previous studies demonstrate that the second order PQL estimation may induce bias on the estimates or encounter convergence problem. A Bayesian approach is therefore an alternative method for parameter estimations (Rodriguez and Goldman, 2001). Unlike the classic frequentist approach estimation methods which have been previously discussed, the Bayesian approach views the unknown parameters as random variables (Gelman *et al.*, 2014). Gelman *et al.* (2014) discuss the advantages of adopting the Bayesian approach in data analysis. The authors point out that this framework is flexible in fitting models with multiple parameters and complex data structure as it can provide a conceptually simple method for handling these complexities. Moreover, Hox (2010) also suggests that a Bayesian approach always produces proper estimates that avoids the problem of negative variance estimates if the correct probability distribution is well defined.

In the Bayesian approach, each of the unknown parameters has a corresponding probability distribution that describes the corresponding uncertainty and contains information about the parameter prior to data collection (Gelman et al., 2014; Browne, 2015). This probability distribution is referred to as the *prior distribution*. After the data are collected, the prior distribution is transformed to a posterior distribution through merging with the data likelihood. The posterior distribution describes the uncertainty about the unknown parameters conditioned on the observed data. Since the observed data contains some extra information on the unknown quantity of interest, the variance of the posterior distribution may be smaller than that of the prior distribution (Hox, 2010). The prior distribution can be either informative or uninformative. An informative prior contains rich information about the uncertainty of the unknown parameters and it can strongly influence the posterior distribution and conclusion. Meanwhile, the uninformative (or diffuse) prior has little influence on the posterior distribution. Therefore, Hox (2010) suggests that it is more preferable to use the diffuse prior to produce the posterior distribution instead of using an informative prior. The point estimates and the corresponding credible intervals (equivalent to the confidence interval in the frequentist approach) of the posterior distribution can only be easily calculated if the posterior distribution has a simple mathematical form. In practice, the posterior distribution generally has a complicated form such that the parameter estimates cannot be calculated mathematically. In this situation, Markov Chain Monte Carlo (MCMC) procedures can be used to approximate the unknown parameters by producing simulated draws from the posterior distribution (Hox, 2010; Goldstein, 2011; Browne, 2015).

The MCMC procedures are simulation-based algorithms that run for many iterations to produce a random sample of values from the posterior distribution for the unknown parameters (Hox, 2010; Snijders and Bosker, 2012; Browne, 2015). At each iteration, a random draw from the posterior distribution is produced based on the values of the previous iteration after convergence. Therefore, the true shape of the posterior distribution can be approximated by obtaining a large number of random draws. Afterwards, the point estimates and the corresponding credibility intervals of the unknown parameters can be obtained from the simulated posterior distribution. As discussed, all unknown parameters are assumed to have prior probability distributions (Gelman et al., 2014). The literature suggests that using diffuse priors and the quasi-likelihood estimates as starting values in the MCMC estimation can produce better and more efficient estimates (Goldstein and Rasbash, 1996; Goldstein, 2011; Browne, 2015). Although previous simulations have demonstrated that a burn-in length of 500 iterations is sufficient for the Markov chain to reach equilibrium (Browne and Draper, 2000;2006), it is often not sufficient in practice especially when the data have a complicated hierarchical structure or many parameters. Convergence assessment, therefore, is important to ensure the Markov chain has converged (Cowles and Carlin, 1996; Brooks and Roberts, 1998; Draper, 2008).

The Deviance Information Criterion (DIC) is used for model selection in a Bayesian approach (Spiegelhalter *et al.*, 2002). It is a generalisation of the Akaike Information Criterion (AIC) which identifies the best fit model from models with different parameters for a given set of responses and priors (Goldstein, 2011). As a Bayesian analogue of AIC, DIC takes into account of the complexity of the additional parameters in the model and a small DIC implies a better model fit(Burnham and Anderson, 2002; Spiegelhalter *et al.*, 2002).

1.5.2.4 Diagnostics for Multilevel Modelling

Multilevel modelling accounts for the clustering structure in the data. Similar to standard linear models, hierarchical linear models are also based on a range of assumptions. In order to produce valid estimates and avoid misspecification of the models, it is important to ensure the underlying assumptions are satisfied by performing relevant diagnostic tests. The following sub-sections will discuss the diagnostics for multilevel models: the residual diagnostics for hierarchical models, the validation of the assumptions for multilevel cumulative ordered logit models as well as diagnostics for models using MCMC estimation.

Residual Diagnostics for Multilevel Models

In hierarchical models, the random effects for each level is assumed to follow a multivariate normal distribution. This is known as the assumption of normality. We can check the assumption by plotting a normal probability plot of the standardised residuals for each level

(Snijders and Bosker, 2012; Hox, Moerbeek and van de Schoot, 2018). An ideal normal probability plot is an approximate straight line.

Multilevel models also assume homoscedasticity of variance of residual errors in all levels (Hox, Moerbeek and van de Schoot, 2018). In a random intercept model, the variances of the random effects for all levels are assumed to be constant. Meanwhile, in a random slope model, the lower-level variance is assumed to be constant even when the higher-level variance is a function of the explanatory variables with a random coefficient. There are different methods to check the assumption of homogeneity of variance. Hox, Moerbeek and van de Schoot (2018) suggest that a scatter plot of the standardised residuals against the predicted values of the outcome can provide information about the assumption of homoscedasticity. The assumption is valid if the residuals scatter around zero.

Validation of the Proportional Odds Assumption for the Multilevel Cumulative Ordered Logit Model

The proportional odds assumption is an important assumption for a multilevel cumulative ordered logit model. Under this assumption, the effects of the explanatory variables on the cumulative odds are assumed to be the same for all categories on the logarithmic scale (Snijders and Bosker, 2012). In order to examine the validity of this assumption, we can compare the multilevel cumulative ordered logit model with a similar model that has the assumption (partially) relaxed (Steele, 2011). If the assumption is valid, there would not be any significant difference between these two models.

Fitting Diagnostics for Multilevel Models using MCMC Estimation

Using a Bayesian approach to estimate multilevel models produces proper and accurate estimates only when the MCMC algorithm has reached a convergence. Sinharay (2004) argues that using the results from an MCMC estimation that has not converged can lead to incorrect inferences. Therefore, it is important to perform an assessment to ensure the convergence of the MCMC estimation (Cowles and Carlin, 1996; Brooks and Roberts, 1998; Sinharay, 2004; Draper, 2008; Gelman *et al.*, 2014; Depaoli and Van de Schoot, 2017; Jones and Subramanian, 2017). To determine whether the algorithm has converged, it is essential to monitor the convergence of all parameters in the model (Van de Schoot and Depaoli, 2014). Failing to check the convergence of all parameters may lead to a premature convergence conclusions (Sinharay, 2004). The convergence diagnostics can be conducted based on graphical methods and statistical criteria. Many articles have been published to discuss different MCMC diagnostic tools which can be used to determine convergence (for example, Cowles and Carlin, 1996; Brooks and Roberts, 1998; Sinharay, 2004; Hamra, MacLehose and Richardson, 2013). Here, we are going to discuss some of the most commonly used diagnostic tools.

The Trace Plots of Estimates can be used to check whether the Markov chain has reached the equilibrium distribution (Jones and Subramanian, 2017). This is one of the graphical methods that allows researchers to visually inspect the chain convergence. A proper trace plot should demonstrate the chain has reached a stationary distribution which wander randomly around the same region of the parameter space (Hamra, MacLehose and Richardson, 2013). If the chain has not converged, more iterations need to be run and the burn-in length needs to be increased (Depaoli and Van de Schoot, 2017).

The Kernel Density Plots of the Posterior Distribution is another visual method to inspect if there are enough samples from the posterior for an adequate representation for the posterior distribution (Hamra, MacLehose and Richardson, 2013; Gelman *et al.*, 2014; Depaoli and Van de Schoot, 2017). It is important for the posterior distribution to be smooth and to make sense from a substantive perspective. Unexpected peaks or an unusual shape in the density plots indicate poor model convergence (Hamra, MacLehose and Richardson, 2013). An ideal density plot would exhibit a symmetric distribution.

The Raftery and Lewis Diagnostic is a method that is based on the theory of Markov chain (Sinharay, 2003;2004). Developed by Raftery and Lewis (1992), it is often used to estimate the length of Markov chain required to accurately estimate a particular quantile (for example, 2.5% and 97.5%) to a given precision (Goldstein, 2011). If the length of chain used in the MCMC algorithm is larger than the lengths estimated by the Raftery and Lewis diagnostic, then we can confirm that the algorithm has converged.

Finally, the *Effective Sample Size (ESS)* provides information on how many independent iterations the Markov chain iterations are equivalent to (Jones and Subramanian, 2017). It suggests whether high correlations exist between subsequent draws. Jones and Subramanian (2017) recommend an ESS of 500 would be enough for most parameters of interests.

1.5.3 Application of Multilevel Modelling

1.5.3.1 Using Multilevel Modelling for the Analysis of Interviewer Effects

As discussed, interviewer effects can contribute to measurement errors and influence how respondents report their answers. Nevertheless, data collected from face-to-face interviewer-administrated surveys are not only clustered within interviewers. Due to the multistage sampling procedure and data collection method, the data are also clustered within sampling units (or geographical areas). Individuals selected from the same sampling units are positively correlated with each other because people who live in the same area can be influenced by the same environmental factors and subjected to similarities in sociodemographic and cultural characteristics of the areas (Vassallo, Durrant and Smith,

2017). The influence of area clustering is often referred to as *area effects* or *sample design effects*. Therefore, it is important to distinguish interviewer effects from area effects when aiming to estimate the influence of interviewers.

In the survey literature, multilevel modelling is a commonly adopted approach to analyse interviewer effects on survey nonresponse and survey response outcome or measurement error. Since both interviewer and area effects can contribute to nonresponse and measurement errors, one option to control for both effects and to disentangle the influences due to the interviewers and areas is the use of an interpenetrated sample design (Campanelli and O'Muircheartaigh, 1999; West and Blom, 2017). Such a design requires respondents to be randomly allocated to interviewers (Schnell and Kreuter, 2005). Using an interpenetrated survey design enable the reduction of subjective interviewer error during survey interview, and the overall standard error of response variances. Since the respondents are randomly assigned to interviewers, the bias by any single interviewer will be relatively equally shared by all the respondents who are allocated to that interviewer (Gillikin, 2008). In this case, it becomes less likely that the behaviour of the interviewers or the way they administrate the questionnaires would induce errors in the responses. Although survey researchers are aware of the benefit of implementing an interpenetrated design, it is very costly and difficult to employ an effective full interpenetrated design in practice. In face-to-face surveys, if each interviewer is allocated to a single geographical area (or sampling unit), the interviewer and area effects are confounded (West and Blom, 2017). To avoid complete confounding of interviewer and area effects, a partial interpenetrated design is often applied. A partial interpenetrated design can be used to separate interviewer from confounded area effects. In order to achieve a partial interpenetrated design, adjacent sampling units are pooled and there should be at least two interviewers randomly allocated to these sampling units (West and Blom, 2017). In practice, many surveys employ a partial interpenetrated design where one interviewer is usually assigned to more than one geographical area and there are more than one interviewer working in one area. As a result, interviewers and areas are no longer perfectly hierarchical but cross-classified. It means that survey responses are clustered within the combinations of interviewer- and area-levels. Failing to incorporate this crossclassified structure in the estimation will lead to misattributed response variation to the included levels and will result in a misleading conclusion about the relative importance of different sources of influence on the response (Leckie, 2013). In order to account for the cross-classified structure, a cross-classified multilevel model can be used. The cross-classified multilevel modelling approach is an extension of a simple hierarchical model that incorporates the random effects for both interviewer and area in a cross-classified structure (Fielding and Goldstein, 2006; Goldstein, 2011). The use of a cross-classified model can improve the estimate of the explanatory variables, identify the variance components in the

outcome, estimate higher-level effects and differentiate the interviewer effect from the area effect (Fielding and Goldstein, 2006). A cross-classified modelling approach has been used in many studies to distinguish between interviewer and area effects (for example, Campanelli and O'Muircheartaigh, 1999; Durrant *et al.*, 2010; Vassallo *et al.*, 2015).

To identify and compare interviewer and area effects on *response rate*, Campanelli and O'Muircheartaigh (1999) apply cross-classified multilevel logistics modelling to Wave 2 of the British Household Panel Study that employs an interpenetrated sample design. In their study, they manage to separate the interviewer effect from the area effect using the cross-classified multilevel model and findings also demonstrates the significance of interviewer effect on survey nonresponse. Meanwhile, Durrant *et al.* (2010) also adopt a cross-classified multilevel approach to examine the interviewer effect on nonresponse and identify what types of interviewers' attributes are important in encouraging survey participations. Analysing data that contain extensive information from the interviewers, which are linked to the responding and nonresponding samples from six UK cross-sectional household surveys, the authors successfully identify significant interviewers' attributes (such as interviewer experience and confidence level) and interviewer-respondent interaction effects which influence people's willingness to participate in a face-to-face survey. Instead of using a fully interpenetrated design, these six cross-sectional household surveys adopt a partial interpenetrated design. Similar results are also obtained by Vassallo *et al.* (2015).

Similar to the effect of interviewers on survey nonresponse, survey response outcomes can also be prone to interviewer and area influences and such influences can also be analysed using a cross-classified multilevel modelling approach. An early study by O'Muircheartaigh and Campanelli (1998) analyse the second wave of the British Household Panel Survey using cross-classified multilevel models to compare the relative impact of interviewer and area effects on survey outcome responses. Their results show that survey outcomes are subjected to both interviewer and area effects. They also identify a range of survey questions related to respondents' behaviours that can be easily influenced by interviewers. Furthermore, using a nested multilevel model approach, Schnell and Kreuter (2005) successfully identify three types of survey questions which can be highly susceptible to interviewer effects: sensitive questions, nonfactual questions and open questions. Both studies show evidence that there are high intra-interviewer correlations in the respondents' responses in a broad range of questions. A more recent study by Turner et al. (2015) further confirms the previous results that interviewers significantly contribute to response variances. Turner et al. (2015) employ a cross-classified multilevel modelling approach on the interviewer data which is linked to the National Travel Survey. They demonstrate that the interviewers' characteristics and personalities are important in explaining interviewer effect on survey response outcomes.

In Wave 4 of the UKHLS, more than 90.6% of interviewers work in three or more PSUs (or geographical areas) while there is around 25% of PSUs are allocated with more than one interviewer. Findings from a recent simulation study conducted by Vassallo, Durrant and Smith (2017) have shown that limited interpenetration is already sufficient to separate interviewer from area effects. Their study investigates how much interpenetration is required for a cross-classified multilevel model to effectively estimate both interviewer and area effects, and results show that a small interviewer dispersion (around three areas per interviewer) is enough to provide sufficient interpenetration for efficient estimation. As most interviewers work in three or more areas in the Wave 4 of the UKHLS, the design can be considered as a limited interpenetration. Therefore, we apply cross-classified multilevel models to account for both interviewer and area influences on response outcomes in Papers 1 and 2. Full mathematical details of the models and information applicable to our data sources are presented in the subsequent papers.

1.5.3.2 Using Multilevel Model for Multi-Country Comparisons

Multi-country surveys, also known as cross-national surveys, are commonly used in social science research, in particular for the purpose of cross-national comparisons (Lynn, Japec and Lyberg, 2006; Kaminska and Lynn, 2016). These surveys, such as the Eurobarometer, International Social Survey Program (ISSP) and European Social Survey (ESS), provide harmonised data for social scientists to investigate and explain differences across countries. For instance, Filippidis et al. (2017) examine the changes in levels of ever use of electronic cigarettes using the Eurobarometer that contains data from 27 European Union member states; Fieldhouse, Tranmer and Russell (2007) investigate the country variations in turnout for young people across Europe using data obtained from ESS; Franzen and Meyer (2010) use the 1993 and 2000 ISSP data to look at the determinants of public concern on natural environment across nations. For cross-country data, individuals are often nested within countries. Because of the hierarchical nature of the data, social scientists often apply a multilevel modelling approach in their studies to examine country and individual effects on the outcomes of interest. Fieldhouse, Tranmer and Russell (2007), Franzen and Meyer (2010) and Filippidis et al. (2017) adopt a multilevel modelling approach in their studies to analyse secondary cross-national data. Although applying multilevel modelling on cross-national data seems to be convenient, scholars have raised concerns from both survey methodological and statistical perspectives. On the one hand, there is always an on-going debate between designand model-based analysis (Groves, 1989). Kaminska and Lynn (2016) highlight the importance of incorporating survey designs and weights in variance estimation when analysing cross-national data. However, some studies argue that ignoring the complex sampling design in analysis produce unbiased estimates (for example, Frohlich et al., 2001;

Solon, Haider and Wooldridge, 2015). On the other hand, the robustness and reliability of multilevel modelling of multi-country data have been challenged. Bryan and Jenkins (2016) raise a question on how many countries are required for a multilevel model to produce correct estimates for country-level effects. In the following paragraphs, the debate between design- and model-based analysis will be discussed, then the potentials and limitations of the use of multilevel modelling on multi-country comparisons will be considered.

Cross-national surveys always employ complex sample designs. Dependent on each country's survey practices, methodological and financial resources, it is common for countries to use different sampling techniques and procedures. In most of the cases, these surveys use a random sampling design. A combination of stratification and multistage sampling design is often adopted (Snijders and Bosker, 2012). Therefore, it is important to take the sampling probabilities into consideration in the data analysis. The sampling probability (also known as inclusion probability) is the probability of an element of the population being included in the sample. In a simple random sampling design, all elements from the population have the same sampling probability. However, the inclusion probabilities for each element from the population can be different in the case of stratification and multistage sampling designs. As a result, failing to incorporate the sampling probabilities in the analysis may lead to a biased representation of the target population. Here, the target population (also referred to as the *inferential population*) is the population to be studied and for which the basic inferences from the survey will be made (Biemer and Christ, 2008). Although a biased representation of the target population does not necessarily lead to bias for the inference, how to handle these sampling probabilities in order to obtain unbiased or approximately unbiased inferences always needs to be considered. To generalise the relationships between variables of interest and other variables to our target population (in other words, to make analytic inference for the target population), we can view the probabilistic nature of the inference from two approaches: model-based approach inference and design-based approach inference. The model-based perspective assumes "data can be regarded as the outcome of a probability model with some unknown parameters" (Snijders and Bosker, 2012, pp. 217) and hence the sampling design becomes peripheral when the model is true and the sampling mechanism is uncorrelated with the residuals in the probability model. Meanwhile, the design-based approach is based on "the probability mechanism used for the sample selection" (Snijders and Bosker, 2012, pp. 218) and therefore it stresses the importance of weights in obtaining unbiased inferences. There are two types of weights: sampling weights and analytical weights. Sampling weights (also known as survey weights) are the inverse of the sampling probabilities and hence provide design-unbiased estimates (Häder and Gabler, 2003). They can be interpreted as the number of population units represented by each unit of the sample (Lohr, 2010). Sampling weights can be used to adjust for different types of biases, such as the

nonresponse bias and non-coverage bias (Biemer and Christ, 2008). Cases that are underrepresented in the sample are often assigned a larger weight. Meanwhile, analytical weights (also known as precision weights) are post-survey weights which aim to reduce sampling variances. These poststratification weights use auxiliary information from other sources to improve the precision of the estimators (Kalton, 1983; Biemer and Christ, 2008). Snijders and Bosker (2012) have an in-depth discussion on whether a model-based or a design-based analysis should be performed on multilevel survey data. They argue that if the sampling design is noninformative (i.e., the residuals in the models are independent of the sampling design), weighted analysis is not necessary. Moreover, multilevel analysis has already accounted for the clustering or multi-stage nature of the sample designs. This is particularly true for multi-country data where a set of countries or a finite population is assumed to be a sample from an infinite population (or the superpopulation). It is suggested that by incorporating design variables in a model-based approach analysis would be more efficient than a design-based analysis where sampling weights are used (Snijders and Bosker, 2012).

In most of the existing cross-country surveys, countries are not randomly sampled from all countries in the world. However, as we have briefly mentioned, the set of countries that participate in the surveys (a finite population) can be viewed as a sample from a superpopulation (an infinite population). Under the assumption that the multilevel model holds for the superpopulation, we can generalise the inferences to a population that is beyond the countries that are present in the survey.

The application of multilevel modelling on cross-national research has also been challenged from a methodological perspective. One of the most debateable questions is: *how many* countries are necessary for a robust multilevel analysis using cross-country data? Many simulation studies have been conducted to determine the minimum number of clusters or groups in order to make proper inferences in a multilevel framework (for example, Maas and Hox, 2005; Rabe-Hesketh and Skrondal, 2012; Stegmueller, 2013; Bryan and Jenkins, 2016; McNeish, 2016). However, the rules of thumb suggested by these studies vary from less than 10 to even 100 groups. Despite the variability, these studies clearly confirm the limitations of having small number of clusters (or small number of countries in cross-country comparison). The basis of the commonly used estimation method, maximum likelihood estimation, is asymptotic and assumes large sample size and hence standard errors for the level-two variances are biased downward (Maas and Hox, 2005). An early study conducted by Maas and Hox (2005) investigates the effect of small number of groups on a random intercept model with only one level-one explanatory variable and one level-two explanatory variable. They show that the standard errors of level-two variances are very sensitive to the number of level-two groups if maximum likelihood estimation is used. Another simulation study

conducted by Stegmueller (2013) expands the scope of the study to include a random coefficient component, as well as considering the effect of small cluster size on a binary outcome. Results show that the maximum likelihood estimates for level-two explanatory variables are biased upward when there are fewer than 20 countries. Meanwhile, maximum likelihood estimates are also severely biased in a random coefficient model even when the number of countries reaches 30. It becomes more problematic when cross-level interactions are included in the model. Hence, Stegmueller (2013) suggests that researchers should be sceptical when making conclusions about cross-level interactions. Bryan and Jenkins (2016) also perform several simulation studies to investigate the effect of a small number of leveltwo clusters on both fixed and random effects in random intercept models and random coefficient models. Compared to the studies conducted by Maas and Hox (2005) and Stegmueller (2013), the specifications of the simulations in Bryan and Jenkins (2016) study include different types of covariates to realise a more practical application. Their findings show that level-one variances and fixed effect parameters are unbiased even when there are few clusters whereas level-two fixed effect parameters exhibit large variability in a random intercept model with a continuous outcome. In terms of level-two variances, the bias becomes negligible when there are more than 30 clusters. Regarding the cross-level interaction, Bryan and Jenkins (2016) demonstrate a similar result as that in the study by Stegmueller (2013). Their results show that when a cross-level interaction is included in the model, both the estimates of the interaction and the level-two effect can be severely affected when the number of clusters is small. Nevertheless, the inclusion of a random coefficient in the model shows that the random slope and level-two variances are biased downward, yet, the bias is less than 2% when there are more than 25 countries. Similar results are also observed in the random intercept model and random coefficient model with a binary outcome. However, the downwardly biases for level-two variance and random slope are more problematic when a binary outcome is considered. Similar results are also reported in the study by Stegmueller (2013). There is much evidence that multilevel model with few clusters (or countries for multi-country comparison) leads to biased inferences, especially on the level-two variances, cross-level interaction terms and random coefficient models. In order to reduce biases and improve inferences, it is suggested that a Bayesian approach can be adopted. Stegmueller (2013) has successfully demonstrated in his simulation studies that by turning to a Bayesian approach, less biased level-two variances can be estimated for both continuous or binary outcomes when there are around 25 to 30 groups (or countries). He also argues that Bayesian intervals are more likely to provide a more conservative conclusion. However, it should be noted that the estimates remain problematic for cross-level interactions even when a Bayesian approach is used. Nevertheless, turning to a Bayesian approach remains a popular choice for cross-national studies using multilevel analysis.

Chapter 2: Identifying Household Effects on Individuals' Environmental Behaviours: A Multilevel Modelling Approach (Paper 1)

2.1 Introduction

2.1.1 Background

Greenhouse gas (GHG) emissions are associated with the global climate change problem. The reduction of GHG and in particular carbon emissions are one of the most important challenges to relieve the pressure from climate change. In order to achieve that aim, the United Kingdom (UK) government has set three GHG emissions targets at both domestic and international levels: Kyoto Protocol, the Climate Change Act 2008 and the EU Effort Sharing Decision (Department of Energy & Climate Change, 2015b). These targets allow the UK government to monitor the change in the GHG emissions and its impacts on climate change.

Human behaviours are one of the causes of GHG emissions. For example, the energy supply sector in the UK contributed to 33% of GHG emissions whereas the transport sector generated 21% of all emissions in 2013 in the UK (Department of Energy & Climate Change, 2015a). The Department for Environment, Food and Rural Affairs (2017) also reports that, among UK consumption related GHG emissions in 2012, 38% was from UK produced goods and services that are consumed by UK residents, 45% was associated with imported goods and services and the remaining 17% was generated directly by UK households. It is clear that people's daily behaviours contribute to GHG emissions directly and indirectly and hence impact directly on the environment and climate change. There is consensus that GHG emissions can be reduced through encouraging and promoting more environmentally friendly behaviours among the public. Behaviours are complex and different behaviours are determined by various inter-related factors. Hence, it is essential to understand the underlying internal and external determinants of the pro-environmental behaviours for the UK government to inform effective policy making (Darnton *et al.*, 2006).

Environmental behaviours have been widely studied from different perspectives and theoretical frameworks (for example, Ajzen and Fishbein, 1980; Anable, 2005; Steg, van de Berg and de Groot, 2012; Heinonen and Junnila, 2014). The Theory of Planned Behaviour (TPB; Ajzen, 1985; 1991) and the Norm-Activation Model (NAM; Schwartz, 1977) are the most commonly used frameworks to study environmental behaviours from a psychological

point of view. These two models, developed in the late 1970s and in the 1980s, provide a fundamental framework in environmental psychology research, based on the assumption that people make rational choices or behave morally in their daily behaviours (Steg and Vlek, 2009). Furthermore, the Value-Belief-Norm Theory of Environmentalism (VBN; Stern, 2000) has been further developed from these existing models to provide a more comprehensive and integrated perspective to study environmental behaviours. These studies emphasise how individuals' sociodemographics, attitudes and values have an impact either on a specific type of environmental related behaviour (for example, Thøgersen, 2006; Barr, 2007) or on a general environmental behaviour (Kaiser and Wilson, 2004; Longhi, 2013) using structural equation and linear regression modelling approaches. However, current research mainly focuses on individual-level influence only. It has been criticised by Longhi (2013) that the complicated relationships between personal attitudes and behaviours with other household members are often ignored. Lynn and Longhi (2011) argue that attitudes and behaviours are likely to be influenced by other household members and therefore the role of households should be taken into account to capture this intra-household dynamic. Current literature on understanding the role of household in individuals' environmental behaviours is scarce as data are usually collected at individual level and lack information about the household members who share the same household setting. One of the available datasets with information at both levels is Understanding Society, the UK Household Longitudinal Study. A recent study by Longhi (2013) using Wave 1 of this dataset investigates the impacts of different household types (such as single households or two-person households with children) on individuals' pro-environmental behaviours by applying separate regression models for different household types, which is equivalent to control for a fixed effect in a single-level model. However, the paper does not incorporate the hierarchical data structure in the analysis to allow for observed and unobserved household level influences.

In household surveys where all eligible members in the household are being interviewed, the individuals are nested within households. This nesting structure results in individual observations being clustered in a higher-level grouping (i.e., household). Since individuals from the same household share some similarities, failing to incorporate this clustered structure in the analysis underestimates the variances of the estimates as the assumption of independence of observations has been violated (Goldstein, 2011). However, no research has taken the hierarchical structure into consideration to analyse household-level effects on environmental behaviours. Moreover, due to the complex multiple-stage sampling design of survey, households are often clustered within both interviewers and geographical areas (or PSUs). If interviewers work in more than one PSU and an area is covered by several interviewers, the data are said to be cross-classified. To date, there has been no study that

incorporates such a cross-classified structure of area and interviewer on individuals' environmental behaviours.

2.1.2 Aims and Methods

This paper analyses individuals' pro-environmental behaviours and identifies the role of household and the underlying factors that influence behaviours using a multilevel modelling framework. In order to account for both interviewer and geographical area effects in the analysis, a cross-classified multilevel model is used.

The analysis is conducted on Wave 4 of Understanding Society, the UK Household Longitudinal Study, a representative national household panel study in the UK. The dataset contains general information at both individual and household levels and questions specifically on environmental behaviours and attitudes at the individual level. The focus of this study is on the overall pro-environmental behaviours, which are measured as a continuous score based on eleven behaviours.

This study uses various sociological and psychological approaches to explain individual and household characteristics that have significant impacts on pro-environmental behaviours, with particular emphasis on individuals' environmental attitudes and the role of household. This study extends the current research scope to a higher hierarchical structure, focusing on the impact of household on individuals' behaviours. This study uses secondary data and therefore some potential factors may not be included in the analysis as the survey data are not collected particularly for this research purpose. Behaviours can be influenced by attitudes but this causal direction can also be reversed. In this study, attitudes are assumed to affect behaviours as it is logical to view one's environmentally friendly behaviours are driven by one's attitudes.

Daily behaviours contribute to GHG emissions both directly and indirectly. Although the effect of an individual's daily behaviour may not be significant, the impact from collective behaviours of a large population becomes significant. By understanding the role of the household in daily environmental behaviours and identifying groups of people that are less likely to behave environmentally, government policies can be targeted to the right group of people to further reduce the GHG emissions in the UK.

This paper consists of five main sections. The data section describes the dataset that is used in the analysis. The methodology section discusses the multilevel modelling approach and the justifications for the method. The results and discussion section presents the findings of the analysis and provides a detailed interpretation of the final model. The limitation section discusses some potential problems about using the data from UKHLS to estimate random

effects. The final section concludes the paper by discussing the implications of this study for policy development and presenting recommendations for future research.

2.2 Data

2.2.1 Overview

This study uses data from Wave 4 of Understanding Society, the UK Household Longitudinal Study (UKHLS) as they are the latest dataset available at the time of this study. It is a longitudinal household survey conducted in the UK, including England, Scotland, Wales and Northern Ireland, covering a representative national sample. This survey gathers information on health, work, education, income, family and social life at both individual and household levels (Knies, 2014). Additional rotating modules are also included at different waves to collect information relating specifically to different topics, for instance, an environmental behaviour module and an environmental attitudes model in Waves 1 and 4, a political engagement module in Wave 3 and a health behaviour module in Waves 2 and 5.

2.2.2 Survey Design

The UKHLS has a complex sample design and consists of multiple components: General Population Sample (GPS), Ethnic Minority Boost Sample (EMBS) and the former British Household Panel Survey (former BHPS) sample. The sampling designs of these three components are different but they all begin with a representative probability sample of households (Lynn, 2009; Knies, 2014).

The GPS is the main component of the study and it is based on an initial sample of 47,520 residential addresses in England, Scotland and Wales and 2,395 addresses from Northern Ireland, resulting in a total of 49,915 households in Wave 1 sample (Lynn, 2009; Knies, 2014). In England, Scotland and Wales, a two-stage sampling design was adopted. A sample of 2,640 primary sampling units (PSUs) stratified by region, social class, population density and ethnic minority density were chosen from the Postcode Address File (PAF), followed by a selection of eighteen PAF addresses using systematic random sampling. On the other hand, an unclustered single-stage design was used in Northern Ireland where addresses were chosen systematically from the Land and Property Services Agency national list of domestic properties.

The EMBS aims to produce an oversample of five main key ethnic groups in the UK (Indian, Pakistani, Bangladeshi, Caribbean and African) by adding 1,000 to 1,125 adults in each of these groups to the GPS (Berthoud *et al.*, 2009; Lynn, 2009). 3,145 postal sectors with

relatively high proportions of the key ethnic groups were selected based on the 2001 Census data and the Annual Population Survey data. A sample of 771 PSUs were selected from these postal sectors after stratification based on the minority density. Among each PSU, 15 to 103 addresses were selected. Finally, interviewers were responsible for the final stage of sampling by following the instructions provided.

The former BHPS sample is included in the UKHLS from the second wave onwards. It contains all members from the 2008 BHPS who were still active at Wave 18 (for *Living in Britain* sample), Wave 10 (for *Living in Scotland* and *Living in Wales* samples) or Wave 8 (for *Northern Ireland Household Panel Survey* sample) and who had not refused consent to be issued to the UKHLS sample (Lynn, 2009; Knies, 2014). These samples include the original sample (1991 BHPS), boost samples in Scotland and Wales (1999 BHPS) and the Northern Ireland sample (2001 BHPS).

2.2.3 Data Collection

The UKHLS is conducted face-to-face by trained interviewers via computer aided personal interviews (CAPI) and self-completion questionnaires. The interview starts with the household CAPI interview which is answered by an adult in the household and follows by an individual interview for each of the eligible adult household members (aged 16 years old or above). In the UKHLS, a household is defined as a person or a group of people who have the accommodation as their only or main residence and share at least one meal a day or share the living accommodation (Lynn, 2009). If an interview cannot be carried out for an eligible respondent, a proxy interview will be conducted by interviewing an adult household member who knows the individual well. From Wave 3 onwards, telephone interviews are also adopted to increase the response rate. At the end of the fieldwork period for each sample month, eligible adults who cannot be interviewed face-to-face by interviewers are contacted by phone. During the face-to-face household interview, eligible household members who are between 10 and 15 years old will be invited to complete a paper youth self-completion questionnaire. Eligible adults are also asked to fill in a separate adult paper self-completion questionnaire (Waves 1 and 2) or to complete a computer administered self-interview (CASI, Wave 3 onwards). Only respondents who complete a productive face-to-face interview are eligible for the self-completion questionnaire.

Data collection usually takes place over a 24-month period (except for the Northern Ireland and the former BHPS samples which are issued over the first 12 months of the wave). Issued samples are spread across the 24-month fieldwork duration and households issued in the first wave (second wave for the former BHPS sample) will be re-interviewed in the same month of the successive years (Knies, 2014).

Two environment related modules are introduced in the first wave of the UKHLS and the same set of questions (with slight modifications) are repeated in the fourth wave. The environmental behaviour module consists of questions related to environmental behaviours which is asked in the face-to-face individual CAPI interview. Meanwhile, the environmental attitudes module asks respondents about their concerns towards environmental issues. These questions are administered on paper self-completion questionnaire (for Wave 1) and CASI (for Wave 4). Both modules are asked at the individual level for eligible adult household members. This paper focuses on the latest available the UKHLS Wave 4 data in which fieldwork is conducted between January 2012 and December 2013.

2.2.4 Interviewers Allocation

Interviewers are well-trained before they conduct an interview. They have to attend a one-day survey specific briefing before they start the fieldwork in addition to the general training (Buck and McFall, 2012). Even though the UKHLS consists of three different samples, interviewers are allocated to households that come from different samples (Jessop and Oskala, 2014). This means that interviewer's assignment can contain a mixture of cases from GPS, EMBS and former BHPS sample. The allocation mechanism is based on two stages: 1) in the first seven months (January 2012 to July 2012), cases are allocated to the interviewers based on geographical proximity to increase field efficiency; and 2) from August 2012 onwards, the focus is shifted to maintain levels of interviewer continuity across waves to maximise the response rates (Buck and McFall, 2012; Jessop and Oskala, 2014). At Wave 4, a total of 692 interviewers are involved in the fieldwork.

2.2.5 Analysis Sample

The dataset contains data from 47,157 individuals coming from 25,831 households, based on the three samples which have been discussed above. Individuals from proxy interviews (n = 3,940) are removed as the environmental behaviour module is not asked during the proxy interview. One of the main focuses of this paper is to investigate the association between environmental attitudes and environmental behaviours. Environmental attitudes are measured in the self-completion questionnaire. Therefore, only individuals with productive interview and complete the self-completion question are included in the initial analysis sample (i.e., a total of 4,265 individuals with productive interview but fail to complete the self-completion questionnaire are removed). Furthermore, cases with missing information on government office region are also dropped (n = 25). The remaining sample is referred to as the full sample which contains 38,927 individuals from 23,818 households from 6,400 PSUs and being interviewed by 637 interviewers. Afterwards, only cases with non-missing

outcome variables are retained in the initial analysis sample. Therefore, the initial analysis sample size is 36,406 from 22,719 households, interviewed by 636 interviewers from 6,241 PSUs. In order to retain a constant analysis sample size throughout the modelling process, an additional category "missing" is added to all the categorical variables which contain item nonresponse. Finally, cases with item nonresponse or missing in potential continuous explanatory variables are listwise deleted. The final analysis sample, therefore, consists of 36,170 individuals from 22,618 households from 6,208 PSUs and interviewed by 636 interviewers. The descriptive statistics of the final analysis sample dataset by potential explanatory variables are included in the Tables A.1 and A.2 of Appendix A.

2.2.6 Data Structure

The UKHLS is a panel household survey, but since this study investigate only Wave 4 data, the data are treated as cross-sectional. As described in the previous section, all eligible members in the issued households are interviewed and this results in a hierarchical structure of individuals being nested within households. Table A.3 in the Appendix A describes the distribution of the number of cases per household based on the final analysis sample (36,170 individuals from 22,618 households). Although around one third of the households in the analysis sample have only one respondent, Rice *et al.* (1998) argue for retaining these households in the analysis since they can contribute to the estimation of the fixed effects. Moreover, findings from previous simulation studies have demonstrated that the proportion of one-respondent households in the sample does not have significant impacts on the estimates (Bell *et al.*, 2010; Bruyndonckx, Hens and Aerts, 2018). Therefore, one-respondent households are retained in the final analysis sample.

Households are then further nested within interviewers and geographical areas. Since there can be more than one interviewer working in one PSU while one interviewer can also be assigned to more than one PSU, households can be classified by both geographical areas where they are located and the interviewers who interviewed them. Here, the geographical areas are the PSUs that the households were selected three years ago in Wave 1 of the UKHLS. Since there is a three-year time gap between Wave 1 and Wave 4, individuals and households may have moved between waves. However, their movements should not bring an immediate change in the area effect for that individual or household as people are more likely to live in communities that share similar socio-economic and cultural factors (Vassallo *et al.*, 2015). This results in a cross-classified structure between the interviewers and PSUs. The distributions of the number of interviewers per area and areas per interviewers based on the full sample are presented in Tables A.4 and A.5 in the Appendix A. There are approximately 75.0% of geographical areas associated with only one interviewer, and more than 90.6% of

interviewers work in three or more geographical areas. Vassallo, Durrant and Smith (2017) have identified by means of a simulation study that the interviewer dispersion can cancel out the effect of interviewer overlap in cross-classified models when interviewers work in more than three areas. Therefore, although the vast majority of areas are covered by only one interviewer, the fact that most of the interviewers work in more than two areas allows cross-classified analysis to separate interviewer effects from the confounded area effects. Furthermore, Bell, Ferron and Kromrey (2008) have demonstrated from their simulation study that with a large number of higher-level units, a large proportion of higher-level units with only one observation have relatively no impact on both the fixed and random effects. Therefore, even though there is a high number of areas with only one interviewer, given that we have more than 600 interviewers working in more than 6,000 areas, a cross-classified multilevel analysis is appropriate to disentangle the interviewer and area effects.

2.2.7 Response Variable

The main focus of this paper is to investigate individuals' pro-environmental behaviour. Eleven questions related to a wide range of environmental behaviours are included in the environmental behaviour module of the questionnaire and they are listed in Table 2-1. For each of these items, respondents are asked to indicate how often they personally engage in the behaviour. Possible answers to these questions are "always", "very often", "quite often", "not very often", "never" and "not applicable, cannot do this". The Cronbach's alpha of these eleven items is 0.538, indicating a modest internal consistency. Similar to the study by Longhi (2013), an overall score of pro-environmental behaviour is computed from the answers of these items.

Table 2-1 List of Pro-Environmental Behaviours in Wave 4 of the UKHLS

- 1 Leave your TV on standby for the night
- 2 Switch off lights in rooms that aren't being used
- 3 Keep the tap running while you brush your teeth
- 4 Put more clothes on when you feel cold rather than putting the heating on or turning it up
- 5 Decide not to buy something because you feel it has too much packaging
- 6 Buy recycled paper products such as toilet paper or tissues
- 7 Take your own shopping bag when shopping
- **8** Use public transport (e.g. bus, train) rather than travel by car
- **9** Walk or cycle for short journeys less than 2 or 3 miles
- 10 Car share with others who need to make a similar journey
- **11** Take fewer flights when possible

Responses to each of the eleven items are recoded to range between zero and four, so that larger value indicates more often the respondents engage in the pro-environmental behaviour. The response "not applicable, cannot do this" is coded as missing. The overall score is the sum of these eleven items. For respondents with less than 25% of item missing among these eleven items (i.e. maximum two item nonresponse in the eleven items) the average for the non-missing items is used to calculate the outcome variable. The score ranges from zero to 44 with higher score indicating more environmentally friendly in daily behaviour. A full description of pattern of missing of the eleven items based on the full sample (N = 38,927) is presented in Table 2-2. The distribution of the outcome of interest based on 36,170 individuals is presented in Figure 2-1, and approximately follows a normal distribution with mean = 20.2, standard deviation = 4.0 and median = 20.0.

Table 2-2 Pattern of Missing Items for the Outcome Score

Number of Missing	Overall (11 items)	
	N	%
0	20,692	53.16
1	10,724	27.55
2	4,990	12.82
3	1,519	3.90
4	645	1.66
5	218	0.56
6	58	0.15
7	53	0.14
8	14	0.04
9	7	0.02
10	2	0.01
11	5	0.01
Total	38,927	100.00

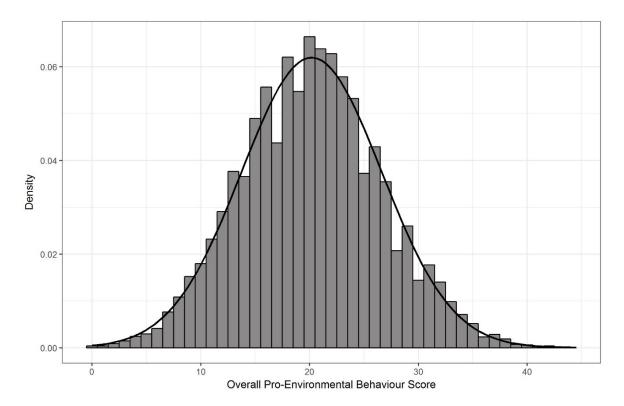


Figure 2-1 Distribution of the Measure of Overall Pro-Environmental Behaviour

2.2.8 Explanatory Variables

The UKHLS contains a wide range of detailed information on both individual and household levels which allows this study to understand the underlying factors for pro-environmental behaviours and to identify the role of household in individuals' behaviours. The environmental attitudes module also enables the study to investigate the influences of individuals' environmental attitudes on their environmental behaviours.

2.2.8.1 Individual-level Variables

Individual Sociodemographics and Personal Values

Information at the individual level includes sociodemographic variables, such as age, sex, marital status, employment status, highest education level, gross monthly income, ethnicity and whether or not the individual is born in the UK. These variables have been found to be highly significant in explaining pro-environmental behaviours in a previous study by Longhi (2013) who analyses Wave 1 of the UKHLS. Personal values have also been highlighted in previous research (for example, Stern *et al.*, 1999; Stern, 2000; Kollmuss and Agyeman, 2002). Therefore, variables related to religion, political orientation and altruistic acts are also used in this study.

Individual Environmental Concern and Attitudes

Individual environmental concern and attitudes have been widely used to explain proenvironmental behaviours (for example, Stern, 2000; Poortinga, Steg and Vlek, 2004; Schultz *et al.*, 2005; De Groot and Steg, 2007). This study uses information from the environmental attitudes module to compute four different measures on environmental attitudes. The first measure is an overall score of environmental concern. It is derived from nine items in which respondents report the extent of agreement toward each of these statements. Table 2-3 lists the nine statements and respondents are asked to select the extent of agreement to these statements from a five-point Likert scale (strongly agree, tend to agree, neither agree nor disagree, tend to disagree and strongly disagree). These nine items have a high internal consistency with Cronbach's alpha of 0.763. Therefore, we derive an additive measure for environmental concern.

Table 2-3 List of Environmental Attitudes Questions in Wave 4 of the UKHLS

- 1 My behaviour and everyday lifestyle contribute to climate change
- 2 I would be prepared to pay more for environmentally-friendly products
- 3 If things continue on their current course, we will soon experience a major environmental disaster
- 4 The so-called 'environmental crisis' facing humanity has been greatly exaggerated
- 5 Climate change is beyond control it's too late to do anything about it
- 6 The effects of climate change are too far in the future to really worry me
- 7 Any changes I make to help environment need to fit in with my lifestyle
- 8 It's not worth me doing things to help the environment if others don't do the same
- 9 It's not worth the UK trying to combat climate change, because other countries will just cancel out what we do

Responses to the nine items are recoded to range between zero and four, so that larger value indicates the respondent has more concerns about the environment. The overall score is calculated by summing up these nine items. For respondents with missing values not more than 25% of all items (minimum two items missing out of nine items), the average for the non-missing items is used to compute the score. The score ranges from zero to 36 where higher score indicating there is more concerns about the environment. The missing pattern of these nine questions are tabulated in Table 2-4.

Table 2-4 Pattern of Missing Items for the Environmental Concern Score

Number of Missing	Overall (9 items)			
	N	%		
0	38,386	98.61		
1	199	0.51		
2	105	0.27		
3	42	0.11		
4	31	0.08		
5	22	0.06		
6	17	0.04		
7	19	0.05		
8	15	0.04		
9	91	0.23		
Total	38,927	100.00		

The environmental attitudes module also includes two items asking respondents to indicate whether or not they agree people in the UK will be affected by climate change in the next 30 and 200 years respectively. These two items are combined into one variable with four categories: 1) people in the UK will not be affected in the next 30 and 200 years; 2) people in the UK will only be affected in the next 30 years; 3) people in the UK will only be affected in the next 200 years; and 4) people in the UK will not be affected neither in the next 30 nor 200 years. Literature has suggested that when people are more aware of the negative consequences of environmental problem, they are more willing to behave more environmentally friendly (for example, Bamberg and Möser, 2007; Steg and de Groot, 2010). Therefore, this derived variable is included in the analysis to represent respondents' awareness of the negative consequences of climate change.

According to the NAM and VBN, responsibility towards environment (or personal norms) is also significant in explaining pro-environmental behaviours (Schwartz, 1977; Stern *et al.*, 1999; Stern, 2000). Therefore, two other variables from the environmental attitudes module that are related to people's perceptions of their current lifestyle and whether or not they would like to do more for the environment are also included in the analysis. These include a binary variable for agreeing being green is an alternative lifestyle and a categorical variable for how willing the respondents would like to alter their current lifestyles to make the environment more sustainable.

2.2.8.2 Household-level Variables

Individuals living in the same household share the same household setting, neighbourhood and household characteristics. As discussed in the previous section, household characteristics, household structure, accommodation characteristics, neighbourhood

characteristics and residential area have shown to be important. Therefore, information at the household-level including household characteristics (car ownership, household gross monthly income), household structure, accommodation characteristics (tenure type and dwelling type), neighbourhood characteristics (trash, litter or junk in street around the neighbourhood and heavy traffic in street around the neighbourhood) and residential area (government office region and urban residence) are included as potential explanatory variables. The neighbourhood characteristics are obtained from two additional pieces of information which is based on interviewers' observations about the neighbourhood when they conduct the fieldwork.

2.2.8.3 Sample Design Variables

As discussed previously, the UKHLS has a complicated multistage survey sample design and it consists of three different sample components (i.e., GPS, EMBS and former BHPS sample). These sample components employ different sampling designs during the data collection stage. According to Snijders and Bosker (2012), incorporating design variables in a model-based approach analysis is as effective as using sampling weights in a design-based analysis. Therefore, we take the sampling design into consideration during analysis by including a categorical variable for the three sample components at the initial stage of modelling so that we can account for the differences in sample structure in these three components. Meanwhile, variables that are used to derive the weights, including the individuals' ethnicity and information about the residential areas (government office region and urban area) are also incorporated in the analysis regardless of their significances.

2.3 Methodology

2.3.1 A Multilevel Modelling Framework

Social science data often have hierarchical or clustered structure, and it is particularly true for survey data. Subject to different sampling procedures, survey data can be clustered in one or more levels. For household survey data, individual responses are nested with households. Meanwhile, in many large-scale interviewer-administrated face-to-face or telephone surveys, sampled households or respondents can also be clustered among interviewers due to the allocations of cases to interviewers or among geographical areas (or PSUs) due to multi-stage sampling. This results in a complicated hierarchical structure on the survey data.

The traditional analysis approach assumes observations to be independent with each other. However, this assumption cannot be applied on the household survey data. Individuals within the same household or households within a PSU (or geographical area) share some

similarities and individuals who are interviewed by the same interviewer are impacted by the interviewer in a similar way. This means that an individual is no longer uncorrelated with another individual in the same group. For example, two individuals living in the same household share the same household characteristics. Higher-level groups (or clusters) and individuals both influence and are influenced by the clusters and consequently, this violates the assumption of independence of observations. Violation of the assumption leads to underestimation of standard errors and therefore gives incorrect inferences (Snijders and Bosker, 2012).

Historically, there are two general approaches that aim to analyse this type of multilevel data, namely the aggregated and the disaggregated approaches. The aggregated approach aggregates the individual data into higher (or macro) level and analyses the macro level by regressing the aggregated means of the predictors on the aggregated mean of the outcome variable. Despite the loss of information during aggregation, this approach tries to analyse the data at the lower (or micro) level and formulate the conclusions at a higher level which can give misleading inferences and conclusions (Hox, 2010). Since relationship between aggregated higher-level units is not the same as the relationship between the lower-level variables, this approach fails to infer the individual relationship from the higher level relationships (Snijders and Bosker, 2012). This fallacy is known as the 'ecological fallacy' (Robinson, 1950) and it has been discussed and well documented in the literature (for example see Alker, 1969; Steel and Holt, 1996; Blakely and Woodward, 2000; Subramanian *et al.*, 2009).

Meanwhile, multilevel data can also be disaggregated in different ways. The first method for the disaggregated approach is the contextual analysis in which data at higher-level units are disaggregated into lower-level units (Hox, 2010). The focus of the analysis becomes at the individual level data by including higher-level predictors. However, this approach assumes all higher-level variances can be explained by the group-level predictors which may not be true and hence gives incorrect estimates for the standard errors of the higher-level explanatory variables (Hox, 2010). The generalized estimating equation (GEE; Liang and Zeger, 1986; Zeger and Liang, 1986) is another disaggregated method to analyses clustered or correlated data. It fits a single-level model on the multilevel data with the standard errors being adjusted for the clustering effect to take the within-group correlation into account. This method assumes a linear model for the expected values of the outcome variable and conditional on the predictors but without assuming any variance or covariance structure (Snijders and Bosker, 2012). Though there is no assumption for the variance and covariate structures, GEE assumes there is independence between these structures at the highest-level cluster (Snijders and Bosker, 2012). Nevertheless, this approach treats cluster as a nuisance rather than as a

focal interest and therefore it does not provide an estimate of the between-group variance (Goldstein, 2011). Compared to the GEE approach, multilevel modelling is a better approach for handling hierarchical data. This approach accounts for the hierarchical structure of the data and unlike the GEE approach, it takes the clustering as an integral aspect of the analysis. Rather than treating the clustering structure as a nuisance, it partitions the residual variation into between-group and within-group components and hence it is able to identify how the total amount of variation contributes to the different level effects (Goldstein, 2011).

2.3.2 An Extension: Multilevel Cross-Classified Modelling

Similar to studying nonresponse in which interviewers and PSUs have found to be significant, individuals' environmental behaviours may also be subjected to these two effects. Variation in behaviours may due to differences between geographical areas (or PSUs) or may subject to the interviewer errors. The way that an interviewer administers the survey may induce errors in the respondents response (Groves, 1989). It has been shown that interviewer effect can lead to substantial measurement errors in survey response, especially for questions related to personal attitudes and social desirable behaviours (Groves, 1989; Hox, de Leeuw and Kreft, 1991; Loureiro and Lotade, 2005; Davis et al., 2010; Gong and Aadland, 2010). Here, measurement error is equivalent to "observational error" and it occurs when there is a difference between the reported and the actual answer (Groves, 1989). However, the survey sample design for face-to-face surveys confounds the interviewer and PSU effects in which a standard multilevel model itself may not be enough to address this complicating factor. Ideally, a fully interpenetrated sample design that implies a completely random allocation of interviewers to sampled cases is able to reduce the subjective interviewer errors (Groves, 1989). Campanelli and O'Muircheartaigh (1999) also show that with the interpenetrated sample design, it becomes possible to separate the interviewer and area effects to some extent. In practice, however, in order to minimise the administrative cost of face-to-face or even of telephone interviews, only a partial interpenetration design is often employed in many household surveys. Though this can avoid a complete confounding of interviewer and area effects, it may not be feasible to fully separate interviewer effects from the PSU effects. In survey implementation, one interviewer may be allocated to more than one PSU and there can also be more than one interviewer working in one PSU. Consequently, this implies an imperfect hierarchical structure of the data. Individuals are fully nested with households, meanwhile, households are also fully nested within interviewers and within PSUs. However, since interviewers are not fully nested within PSUs, there is a cross-classified structure between the interviewer and the PSU. A multilevel cross-classified model, therefore, is able to incorporate this structure in the analysis as it allows a unit to be classified across more than one level (here, household can be classified both by interviewers and by areas) (see

Goldstein, 2011, p.243-251). This approach has been widely used by other authors who study interviewer effect on nonresponse to distinguish the influence of interviewer from the PSU effect (O'Muircheartaigh and Campanelli, 1998; Durrant *et al.*, 2010; Vassallo *et al.*, 2015). Therefore, the multilevel cross-classified modelling approach is adopted in this study separate the household effect from the possible confounding influences from interviewers and areas.

2.3.3 Model Specification

Let $y_{ij(kl)}$ denote the continuous outcome variable of interest (i.e., the general proenvironmental performance) for individual i from household j, interviewed by interviewer k and sampled in PSU l three years ago. The general form of the multilevel cross-classified model can be written as:

$$y_{ij(kl)} = \beta_0 + \mathbf{\beta}_1^{\mathrm{T}} \mathbf{X}_{ij(kl)} + u_i + v_k + w_l + e_{ij(kl)}$$

where $\mathbf{X}_{ij(kl)}$ is a vector of individual-, household-, interviewer-, and PSU-level (or geographical area-level) covariates and interactions; (kl) indicates the cross-classification structure between interviewer k and PSU l; β_0 is the overall intercept in the linear relationship between the outcome and the predictors specified in the model and β_1 is a vector of coefficients for the explanatory variables $\mathbf{X}_{ij(kl)}$. The parameters u_j , v_k , w_l and $e_{ij(kl)}$ are the random effect terms, representing the random effects for household, interviewer, area and individual respectively. These random effect terms are assumed to follow a normal distribution with a zero mean and the corresponding variances, i.e., $e_{ij(kl)} \sim N(0, \sigma_e^2)$, $u_j \sim N(0, \sigma_u^2)$, $v_k \sim N(0, \sigma_v^2)$ and $w_l \sim N(0, \sigma_w^2)$. These variance parameters σ_e^2 , σ_u^2 , σ_v^2 and σ_w^2 are assumed to be mutually independent and identically distributed. They represent the between-individuals (or within-households), between-households, between-interviewers and between-areas variances respectively.

The Variance Partitioning Coefficient (VPC) can be calculated for different hierarchical levels (Goldstein, 2011). It is a measurement of the proportion of total variance contributed to the differences between the corresponding levels. The VPCs for individual, household, interviewer and area levels can be written as:

$$\text{VPC}_{\text{individual}} = \frac{\text{between individual variation}}{\text{total variation}} = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2}$$

$$VPC_{\text{household}} = \frac{\text{between household variation}}{\text{total variation}} = \frac{\sigma_u^2}{\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2}$$

$$\begin{aligned} \text{VPC}_{\text{interviewer}} &= \frac{\text{between interviewer variation}}{\text{total variation}} = \frac{\sigma_v^2}{\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2} \\ \\ \text{VPC}_{\text{area}} &= \frac{\text{between area variation}}{\text{total variation}} = \frac{\sigma_w^2}{\sigma_e^2 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2}. \end{aligned}$$

The VPC is equivalent to the intra-unit correlation. It ranges from zero to one where zero indicates there is no variation between the corresponding levels and one indicates there is no within-level difference.

2.3.4 Model Estimation and Modelling Strategy

The models are estimated by Markov Chain Monte Carlo (MCMC) methods in the MLwiN software (Browne, 2014). The estimates obtained by iterative generalised least squares (IGLS) estimation from fitting a two-level hierarchical model are used as the starting values in the MCMC estimation (Goldstein, 2011). MCMC estimation is a simulation method based on the Bayesian framework to generate draws from the posterior distribution. The point estimates and the corresponding credible intervals are then computed from this posterior distribution (Hox, 2010). This approach is more preferable than the traditional methods, such as IGLS and maximum likelihood (ML) estimations as the multilevel cross-classified model is often more easily estimated within the Bayesian framework (Snijders and Bosker, 2012). The MCMC approach may also have better properties than the approximations to some of the traditional ML methods so it provides better estimates (Goldstein, 2011; Snijders and Bosker, 2012). Since the estimates from the MCMC estimation are always proper when the correct probability distribution is defined, the problem of negative variance estimate that may arise in traditional methods can also be avoided (Hox, 2010).

The proposed cross-classified multilevel model is applied to Wave 4 of the UKHLS data. All the estimations are performed on MLwiN Version 2.25 with default priors, a burn-in length of 5,000 and 500,000 iterations. This burn-in length and number of iterations have been examined by Vassallo, Durrant and Smith (2017) and they demonstrate that such a combination is appropriate to avoid undue influence from the starting values and to provide accurate point estimates and 95% credible intervals.

Model building begins with only one random term at the lowest level (i.e., the individual level). Higher level random effects are then added to the model and tested for significance, resulting in a multilevel cross-classified null model. The random effects are examined using the Wald Test. As discussed by Snijders and Bosker (2012), one-sided *p*-values are used here as variances cannot be negative. Moreover, the *p*-values should also be halved when testing the significance of the random term (Snijders and Bosker, 2012). In order to adjust for the

unequal selection probabilities, differential nonresponse and potential sampling error, sample weights would normally need to be used in the analysis (Knies, 2014). However, MLwiN does not support the use of weight in MCMC estimation (Centre for Multilevel Modelling, 2015). Therefore variables related to the sample composition and used in the models to derive the sample weights are included in the analysis. These variables include sampling composition (GPS, EMBS and former BHPS sample), residential areas (government office regions and urban residence) and ethnicity. Variables related to the sample composition and residential areas are first included in the null model before actual model building. Since all these variables are related to sample weights, they are all included in the final model regardless of their significances in order to account for some key elements of the variation in selection probabilities. However, it should be noted that these variables do not account for all variations that is contributed by the selection probabilities.

Model construction is based on forward selection. After identifying the random structure specification of the model, blocks of explanatory variables are included in the model as fixed effects. Individual level explanatory variables are first considered (in the following order: sociodemographics, personal values and environmental concerns and attitudes), followed by the household level variables (in the following order: household sociodemographics, household structures, accommodation characteristics and neighbourhood characteristics). Finally, interaction terms (including: urban area with ownership of car, urban area with government office regions, urban area with neighbourhood characteristics, government office regions with education level, government office regions with ethnicity and education level with individual income) are also considered. The deviance information criterion (DIC) is used for model comparison (Snijders and Bosker, 2012). A smaller DIC indicates a better fit and hence a more preferable model. Meanwhile, the Wald test is used as the multi-parameter test for fixed effects which allows several regression parameters for a categorical variable to be tested simultaneously (Snijders and Bosker, 2012). It is used to examine the significance of each predictor variable within each block of explanatory variables. The least significant variable with *p*-value larger than 0.05 will be removed from the model, and the model will be re-run until all variables retained in the block are statistically significant at the 5% level. Lower-level variables that have been included in the model previously may become insignificant when higher-level variables are added. In such a case, these insignificant lowerlevel variables will be removed.

In this analysis, sample composition, residential areas, ethnicity and the presence of particular types of household members (pensioner, child younger than two years old, child aged between three and four, five and eleven, and twelve and fifteen) are included in the model as control variables even though some of these variables may not be significant.

2.3.5 Model Validations and Diagnostics

After the final model is obtained, relevant model diagnostic tests are performed to ensure the model assumptions are met. In order to assess the assumption of normality, normal plots for the standardised residuals are created for individual-, household-, interviewer- and PSU-levels (see Figure A.6.1). Meanwhile, standardised residuals are plotted against the predicated value to test the assumption of homogeneity of variance (see Figure A.6.2). All these normal plots and residual plot show that the final model has met both assumptions of normality and homogeneity of variance. Finally, trace plots, and kernel density plots for the posterior distributions for the final models are presented in Figure A.6.3. The effective sample sizes and Raftery-Lewis diagnostics statistics are summarised in Table A.6.4. These plots and statistics indicate that the MCMC algorithm has converged.

2.4 Results and Discussion

2.4.1 Exploration of Random Effects Specifications

Model construction starts with one random effect at the individual level and additional levels are included in the model one-by-one. Since individuals are nested among households and households are further nested among interviewers and geographical areas, the random effect at the household level is first added to the model before the possible inclusion of the cross-classified structure between the Interviewers and PSUs. Table 2-5 shows that the addition of a household random effect (Model 1) has a smaller DIC than the empty model (Model 0). As a model with lower DIC corresponds to better and effective variance estimates, the two-level hierarchical model (Model 1) is considered to have a better fit than the model with only individual random effects (Model 0).

Then two separate three-level hierarchical models (Model 2 and Model 3) are explored by including random effects at PSU and interviewer level. Both models have a smaller DIC statistics compared to that of Model 1, demonstrating that the inclusion of either PSU or interviewer is more efficient in explaining the total variation in the model.

Table 2-5 Variances and DICs for the Multilevel Models

Model	Random Term in the Model	Term	Variance	(S.E.)	DIC
0	None	Individual	41.442	(0.308)***	237,354.5
1	Household	Individual	21.710	(0.262)***	226,862.2
		Household	20.001	(0.372)***	
2	Household and PSU	Individual	21.728	(0.262)***	226,526.0
		Household	16.337	(0.374)***	
		PSU	21.728	(0.262)***	
3	Household and Interviewer	Individual	21.732	(0.260)***	226,430.7
		Household	15.216	(0.372)***	
		Interviewer	4.837	(0.272)***	
4	Household, PSU and	Individual	21.758	(0.261)***	225,929.3
	Interviewer cross-classified	Household	15.061	(0.358)***	
		Interviewer	3.799	(0.294)***	
		PSU	1.193	(0.171)***	

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

A multilevel cross-classified model takes into account the cross-classified structure between the interviewers and PSUs. When the cross-classification is considered in the multilevel model, the DIC statistics further decreases as shown in Table 2-5. The household random effect variance is reduced by approximately 25% in comparison to the variance estimated for the two-level model which includes only the household effect (Model 4 compared to Model 1). The interviewer and PSU effect variances are partitioned from the household effect variance. Despite the decrease in household random effect variance, this random term remains statistically significant ($\chi^2(1) = 1,770, p < 0.001$). The inclusion of the cross-classified structure does not have any effect on the individual variance whereas the interviewer random effect ($\chi^2(1) = 167, p < 0.001$) and area random effect ($\chi^2(1) = 49, p < 0.001$) are both significant.

In conclusion, a multilevel cross-classified model is an appropriate model to address the research question in this study. It is obvious that the household has an impact on individuals' environmental behaviours after controlling for interviewer and geographical area effects.

2.4.2 Discussion of the Final Model - Random Effects

One main focus of this paper is to identify the role of households in individuals' environmental behaviours. Therefore, it is essential to examine how individual and household influence behaviours differ. We aim to explain the random variation by introducing individual- and household-level variables. Table 2-6 shows the estimates of the individual, household, interviewer and PSU random effects, the corresponding VPCs and DIC statistics as blocks of explanatory variables are included in the null model (Model 4).

As blocks of explanatory variables are included in the multilevel cross-classified model, the DIC statistics decreases substantially from 225,929 to 221,903, indicating that the inclusion of the fixed effects increases the goodness of fit of the model. Meanwhile, the individual, household-, interviewer- and PSU-level random effects remain significant.

For the null model without any fixed effect explanatory variable, the individual variance accounts for around 52% [21.758/(21.758+15.061+3.799+1.193)] of the total variation. After controlling for the sampling design variables (sampling composition, government office region and residential area), the individual-level VPC increases to 54%. Once the individual level variables (sociodemographics, personal values and environmental attitudes) are added to the model, the VPC due to the individual level is increased to 59% as these variables explain parts of the between-individual variation. The inclusion of household level variables (sociodemographics, household structure, accommodation characteristics and neighbouring characteristics) further increases the VPC to 61% (see Table 2-6). This indicates that parts of the individual differences can also be explained by these household level variables.

Meanwhile, the household variance accounts for 36% of the total variation when none of the fixed parameters are present in the null model. The household-level VPC increases slightly to 37% after the sampling design variables are controlled for. The VPC decreases to 30% when variables at individual and household levels are added. Furthermore, once the individual-level variables enter the null model, the household random effect variance decreases from 15.0 to 11.6 (23%). On the other hand, there is a further reduction of 13% in the household random effect variance when the household-level variables are included. Surprisingly, there are more substantial reductions in the household random effect when including individual-level variables than the inclusion of the household-level variables (comparing 23% with 13%). This may be explained by the fact that households consist of individuals that share similar characteristics and attitudes and hence the household effect can be viewed as aggregated individual effects. To provide evidence for the hypothesis, sub-analyses are performed in the following sub-section.

Interviewer and area also play an important role in the variation being explained. Table 2-6 also presents the estimates and VPCs of the interviewer and PSU random effects as blocks of explanatory variables are included in the cross-classified multilevel null model (Model 4). For the null model without any fixed effect explanatory variable, the interviewer and area variances account for around 9% and 3% of the total variation respectively. Both random effect variances are significantly smaller than the household random effect, yet, they remain significant. In particular, the interviewer and PSU random effect variances decrease substantially when information on the government office region is included in the model. This can be explained by the allocation mechanism of cases that interviewers are assigned to

households based on geographical proximity. Moreover, it also suggests that there is sufficient interpenetration in the survey implement to separate these two random effects.

Sub-analysis on the Associations between Individuals within Households

In order to investigate why the individual-level variables reduce the household random effect more than the household-level variables, a sub-sample of households consisting of two adults who have completed the interviews (regardless of their relationships and whether or not they are living with children in the same households) are selected specifically to examine whether there is any strong association between individuals within households for some of the individual-level explanatory variables. The sub-sample consists of 8,979 households and 17,958 individuals in total.

In order to assess the within-household agreement for the categorical explanatory variables and continuous explanatory variables, Cohen's kappa statistics and a two-level hierarchical model are used. Cohen's kappa coefficient (Cohen, 1960) is calculated for the nominal and binary categorical predictor variables, including employment status, ethnicity, whether or not born in the UK, political affiliation, involvement in voluntary work, donation to charity, believe in the effect of climate change in the UK and believe green is an alternative living style. The weighted Cohen's kappa coefficient (Cohen, 1968) which is based on Cohen's kappa coefficient is applied to ordinal categorical variables, which include highest education level, level of interest in politics and personal thoughts on current lifestyle and the environment. Finally, a two-level hierarchical model is used to examine the role of the household in the environmental concern score which is measured as a continuous variable.

The Cohen Kappa and weighted Cohen Kappa statistics are presented in Tables 2-7 and 2-8. Rules suggested by Landis and Koch (1977) are used as threshold level to decide whether the individuals within the household have similar responses for the selected individual-level categorical explanatory variables. All these variables have significant Cohen Kappa or weighted Cohen Kappa statistics. There is strong evidence suggesting that among two-adult households, individuals are very likely to share the same education level, ethnicity, immigrant status and political affiliation. Meanwhile, individuals are also likely to have similar employment status, level of interest in politics, involvement in voluntary work and engagement in charity donation. The estimated variance and VPC of the household random effect for the two-level model for the environmental concern score is shown in Table 2-9, demonstrating that the household explained 36% of the total variation of the individual concern score.

Table 2-6 Estimates of the Individual, Household, Interviewer and PSU Random Effect Variances as Blocks of Explanatory Variables are added to the Cross-classified Multilevel Model

Fixed Effects Parameters (no. of parameters)	Indiv	mates of the idual Rand ect Variance	ndom Household Randon		dom	Estimates of the Interviewer Random Effect Variance		Estimates of the PSU Random Effect Variance		DIC			
	Variance	(S.E.)	VPC	Variance	e (S.E.)	VPC	Varianc	e <i>(S.E.)</i>	VPC	Variance	e <i>(S.E.)</i>	VPC	
None	21.758	(0.261)***	0.520	15.061	(0.358)***	0.360	3.799	(0.294)***	0.091	1.193	(0.171)***	0.029	225,929.3
Added sampling design (14)	21.772	(0.262)***	0.540	15.029	(0.357)***	0.373	2.377	(0.208)***	0.059	1.166	(0.168)***	0.029	225912.6
Added individual sociodemographics (24)	21.190	(0.255)***	0.554	13.710	(0.338)***	0.359	2.279	(0.198)***	0.060	1.037	(0.155)***	0.027	224,603.0
Added individual personal value (22)	21.061	(0.254)***	0.572	12.725	(0.330)***	0.345	2.174	(0.188)***	0.059	0.890	(0.149)***	0.024	224,014.2
Added individual environmental value (10)	20.637	(0.249)***	0.588	11.593	(0.315)***	0.330	2.085	(0.179)***	0.059	0.773	(0.139)***	0.022	222,891.7
Added household sociodemographics (2)	20.472	(0.244)***	0.612	10.197	(0.294)***	0.305	2.095	(0.177)***	0.063	0.678	(0.131)***	0.020	221,975.3
Added household structure (8)	20.444	(0.244)***	0.612	10.203	(0.295)***	0.305	2.092	(0.176)***	0.063	0.678	(0.131)***	0.020	221,939.5
Added accommodation characteristic (10)	20.445	(0.244)***	0.613	10.126	(0.292)***	0.304	2.091	(0.176)***	0.063	0.667	(0.128)***	0.020	221,906.9
Added neighbourhood characteristic (2)	20.443	(0.243)***	0.613	10.129	(0.292)***	0.304	2.094	(0.177)***	0.063	0.660	(0.129)***	0.020	221,902.9

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 2-7 Cohen Kappa for Selected Individual-Level Explanatory Variables of the Sub-Sample

Variable	Cohen Kappa	(S.E.)	Strength of Agreement
Employment Status	0.369	(0.006)***	Fair
Ethnicity	0.742	(0.008)***	Good
Born in the UK	0.501	(0.011)***	Moderate
Party affiliation	0.463	(0.005)***	Moderate
Involve in voluntary work	0.301	(0.011)***	Fair
Donation to charity	0.326	(0.011)***	Fair
Believe in the effect of climate change in the UK	0.123	(0.008)***	Poor
Believe green is an alternative living style	0.185	(0.011)***	Poor

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 2-8 Weighted Cohen Kappa for Selected Individual-Level Explanatory Variables of the Sub-Sample

Variable	Weighted Cohen Kappa	(S.E.)	Strength of Agreement
Highest education level	0.451	(0.011)***	Moderate
Level of interest in politics	0.314	(0.011)***	Fair
Thoughts about current lifestyle and the environment	0.136	(0.011)***	Poor

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 2-9 Variance and VPC for the Two-level Models for the Environmental Concern Score of the Sub-Sample

Random Term in the Model	Term	Variance	(S.E.)	VPC
Household	Individual	18.931	(0.283)***	0.659
	Household	9.808	(0.320)***	0.341

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

These sub-sample analyses suggest that household members share similar individual sociodemographics, personal values and environmental concerns. Therefore, it explains why the individual-level variables manage to reduce the household-level random effect.

2.4.3 Discussion of the Final Model - Fixed Effects

The estimated coefficients for the final multilevel cross-classified model are presented in Table 2-10. The significant individual level explanatory variables will be discussed with reference to the previous research and literature, followed by the discussion of the variables at household level. It should be noted that in the following sub-section, the interpretation of the fixed effect covariates is conditional on the presence of all other fixed effects in the model.

Table 2-10 Estimated Coefficients for the Final Multilevel Cross-Classified Model on Pro-Environmental Behaviour Score

Variable	Category	β	(S.E.)
(Reference Category)			
Intercept		15.254	(0.610)***
<u>Individual</u>	Sociodemographic Variables		
Age (16-30)	31-45	0.950	(0.099)***
	46-60	1.218	(0.102)***
	61-75	1.569	(0.172)***
	76 or above	1.020	(0.226)***
Gender (Male)	Female	0.700	(0.058)***
Employment Status (Employed)	Self-employed	-0.626	(0.115)***
	Unemployed	0.271	(0.151)
	Retired	0.664	(0.139)***
	Full-time Student	0.952	(0.161)***
	Other Employment Status	-0.152	(0.112)
	Missing	-8.454	(5.252)
Highest education level (Degree)	Other Higher Degree	-0.448	(0.103)***
	A-level or Equivalent	-0.700	(0.092)***
	GCSE or Equivalent	-0.834	(0.095)***
	Other Qualification	-0.946	(0.123)***
	No Qualification	-0.785	(0.127)***
	Missing	-0.369	(0.324)
Ethnicity (White)	Mixed	-0.559	(0.251)*
	Asian	0.197	(0.181)
	Black	-0.569	(0.221)*
	Other Ethnic Group	0.190	(0.391)
	Missing	-0.163	(0.367)
Born in the UK (Yes)	No	1.211	(0.115)***
	Missing	0.257	(0.231)
Individual monthly income	Log transformed income	0.491	(0.058)***
	Quadratic term of log transformed income	-0.080	(0.006)***

Variable	Category	β	(S.E.)
(Reference Category)			
<u>Individual Pe</u>	ersonal Value Variables		
Level of interest in politics (Very	Fairly	-0.320	(0.104)**
interest)	Not very	-0.711	(0.110)***
	Not at all interested	-1.247	(0.119)***
	Missing	-0.215	(1.523)
Supported party (Conservative)	Labour	-0.024	(0.093)
	Liberal Democrat	0.624	(0.135)***
	Scottish National Party	0.050	(0.243)
	Plaid Cymru	0.389	(0.394)
	Green Party	2.300	(0.181)***
	Ulster Unionist	0.610	(0.370)
	SDLP	-0.404	(0.401)
	Alliance Party	1.348	(0.473)**
	Democratic Unionist	0.033	(0.379)
	Sinn Fein	-0.206	(0.437)
	Other party	-0.102	(0.105)
	Cannot vote	0.332	(0.220)
	None	0.611	(0.175)***
	Missing	0.334	(0.129)**
Voluntary work in the last 12 months	No	-0.858	(0.076)***
(Yes)	Missing	6.881	(5.622)
Donation to charity in the last 12	No	-0.451	(0.069)***
months (Yes)	Missing	-1.141	(1.335)
<u>Individual Envir</u>	onmental Value Variables		
Environmental concern	Environmental Concern Score	0.201	(0.006)***
Believe in the effect of climate change in the UK (UK will not be affected in the	UK will only be affected in the next 30 years	0.569	(0.226)*
next 30 and 200 years)	UK will only be affected in the next 200 years	0.065	(0.125)
	UK will be affected in the next 30 and 200 years	0.485	(0.107)***
	Missing	0.648	(0.263)*
Believe green is an alternative living	Disagree	0.646	(0.062)***
style (Agree)	Missing	0.079	(0.337)
Thoughts about current lifestyle and	Would like to do bit more	0.035	(0.066)
the environment (I'm happy with what I	Would like to do lots more	0.442	(0.143)**
do at the moment)	Missing	-1.872	(1.388)
<u>Household Soc</u>	<u>iodemographic Variables</u>		
Ownership of car(s) (Yes)	No	3.749	(0.108)***
	Missing	0.303	(0.956)

ariable Category		β	(S.E.)					
(Reference Category)								
Household Structure Variables								
Pensioner(s) in household (Yes)	No	-0.038	(0.132)					
Children aged 0-2 in household (Yes)	No	0.345	(0.14)*					
Children aged 3-4 in household (Yes)	No	-0.088	(0.144)					
Children aged 5-11 in household (Yes)	No	-0.249	(0.114)*					
Children aged 12-15 in household (Yes)	No	-0.041	(0.125)					
Household structure (Single household without children)	Single household with children	-0.667	(0.200)***					
	Non-single household without children	-0.254	(0.101)*					
	Non-single household with children	-0.385	(0.153)*					
Household Accommo	dation Characteristics Variable	<u>es</u>						
Tenure type (Home owned outright)	Home owned with mortgage	-0.692	(0.099)***					
	Home social rent	-0.716	(0.127)***					
	Home private/ employer rented	-0.301	(0.133)*					
	Other	-0.098	(0.822)					
	Missing	0.194	(0.362)					
Dwelling type (Detached house)	Semi-detached house/ bungalow	0.295	(0.094)**					
	End terraced/ terraced house/ bungalow	0.530	(0.103)***					
	Flat/ maisonette	0.584	(0.144)***					
	Others	0.301	(0.370)					
	Missing	-0.348	(0.783)					
<u>Neighbourhoo</u>	d Characteristic Variables							
Trash, junk and rubbish on the street in	No	0.489	(0.219)*					
the neighbourhood (Yes)	Missing	1.296	(0.792)					

Variable	ariable Category		(S.E.)
(Reference Category)			
<u>Samplir</u>	ng Design Variables		
Sample composition (GPS)	Former BHPS	-0.033	(0.102)
	EMBS	-0.090	(0.177)
Government office region (North East)	North West	0.222	(0.404)
	Yorkshire and the Humber	0.675	(0.420)
	East Midlands	0.724	(0.424)
	West Midlands	0.151	(0.430)
	East of England	1.257	(0.406)**
	London	1.985	(0.401)***
	South East	1.111	(0.396)**
	South West	1.298	(0.440)**
	Wales	1.478	(0.436)***
	Scotland	0.073	(0.435)
	Northern Ireland	-1.344	(0.461)**
Residential Area (Urban)	Rural	-0.200	(0.095)*

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

2.4.3.1 Significant Individual-level Variables

A variety of individual-level explanatory variables are found to be significant in explaining pro-environmental behaviours. The following sub-section discusses the effects of individual-level variables (in the following order: sociodemographics, personal values and environmental attitudes and concerns) on individuals' pro-environmental behaviours.

Individual Sociodemographics

The significant individual-level sociodemographic variables include the following: age, gender, employment status, education level, ethnicity, whether or not born in the UK and the individual monthly income. These variables are found to be significant in explaining individuals' environmental behaviours.

Age

There is an age effect on the pro-environmental behaviours. Older people are found to be more environmentally friendly than the younger group. In particular, those who are 46 to 60 years old and 61 to 75 years old on average have 1.2 points and 1.6 points higher pro-environmental scores than those who aged between 16 and 30. This result agrees with some earlier findings (Pinto *et al.*, 2011; Swami *et al.*, 2011) that report the older people engage more in pro-environmental behaviours than the younger people. It also supports the argument by Gifford and Nilsson (2014) that people who have experienced war time (1937 to

1945) and post-wartime (mid-1940s to early 1950s) periods are more likely to behave environmentally responsible than the younger generation.

Gender

There is a strong gender difference in the participation of pro-environmental behaviours. The result shows that females are more likely to engage in environmentally friendly behaviours than males. On average, women are 0.70 points higher than men in the pro-environmental score and this result is widely supported by previous studies that women tend to behave more pro-environmentally across age groups and countries (for example, Zelezny, Chua and Aldrich, 2000; Luchs and Mooradian, 2012; Scannell and Gifford, 2013). Zelezny, Chua and Aldrich (2000) use the socialisation theory to explain why there is such a gender difference. They suggest that females are usually shaped by the gender expectation in the cultural norms and hence they tend to have a higher level of socialisation and more social responsible than male. Therefore they are more likely to involve in altruistic behaviours, here, the proenvironmental behaviours.

Economic Activities

Self-employed people are less environmentally friendly behaved than employed ones. Meanwhile, retired people and full-time students are more likely to engage in proenvironmental behaviours than the employed people. Full-time students, in particular, have on average 0.952 points higher pro-environmental behaviour score than the employed people when other covariates are kept constant.

A log transformation has been applied to individual monthly income to account for the skewed distribution. The quadratic term for the log-income is also included in the analysis to allow for a non-linear relationship between individual income and the outcome variable. There is a positive relationship between the linear term and the pro-environmental score while a negative relationship is observed between the quadratic term and the outcome of interest. Figure 2-2 shows the predicted mean of the pro-environmental score for an individual at reference category with gross monthly income between £0 and £15,000. As people's income increases, they tend to participate in more environmentally friendly behaviours. However, the tendency diminishes as their earnings increase.

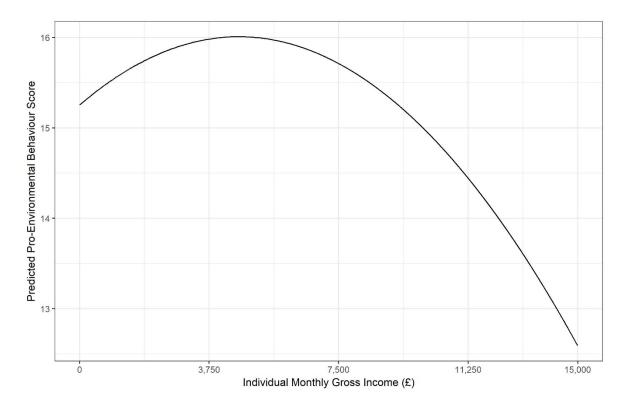


Figure 2-2 Predicted Mean for the Pro-Environmental Behaviour Score across Individual Monthly Income

Highest Education Level

Although literature discusses that education is not necessarily associated with how an individual engage in pro-environmental behaviours, this study demonstrates that less educated people are less likely to behave pro-environmentally and people who received more education tend to participate more in behaviours that benefit the environment. This result also agrees with some previous findings that more educated people usually have more knowledge on environmental problems and are more likely to acknowledge the potential actions to protect the ecosystem (Kollmuss and Agyeman, 2002; Robelia and Murphy, 2012). According to the NAM, environmental behaviours are initiated when an individual is aware of the problems that he or she may have created and acknowledge the correct methods to address the problems. Therefore, it is not surprising to see more educated people behave more environmentally friendly.

Ethnicity

People from mixed and black communities behave less environmentally friendly than the white. Meanwhile, people who are born outside the UK are more likely to engage in proenvironmental behaviours than the native born. This result is consistent with the findings of Longhi (2013) who analyses the first wave of the UKHLS that immigrants seem to have higher pro-environmental behaviours than those who are born in the UK. Furthermore, as previous literature indicates, cultural differences between ethnic group can be used to explained the

differences in pro-environmental behaviours (Johnson, Bowker and Cordell, 2004; Ellis and Korzenny, 2012). Our study has also provided evidence of this impact.

Individual Personal Values

Participation in voluntary work and donation to charity are highly significant in explaining pro-environmental behaviours. People who volunteer for the community or contribute donation to charity are more altruistic than those who are not. According to the VBN, altruistic values are positively related to people's belief on environmental issues (Stern, 2000). Therefore, it can explain why those who engaged in voluntary work and donations are more pro-environmentally behaved.

Level of interest in politics also explain pro-environmental behaviours. Those who show more interest in politics tend to behave more environmentally friendly than those who are not at all interested. Raymond, Brown and Robinson (2011) and Scannell and Gifford (2013) have demonstrated that if an individual has a strong attachment to a place, he or she would want to protect it by behaving appropriately. People who are interested in local politics are usually those who have a strong attachment to their communities. Hence, they tend to engage more in pro-environmental behaviours as they want to protect or improve the places that they are living.

A study conducted in the US has shown that people who have conservative political views are less environmentally concerned than those who have a liberal view (McCright and Dunlap, 2013). The finding from this study is also consistent with the finding that people who support Liberal Democrat (in England) and Alliance Party (in Northern Ireland) are more proenvironmental behaved than those supporting the Conservative Party. Furthermore, the Green Party's supporters have on average a pro-environmental score that is 2.30 points higher than the score of the Conservative Party supporters.

Individual Environmental Concerns and Attitudes

As expected, people with higher environmental concern scores behave more environmentally friendly. The TPB (Ajzen, 1985;1991) can be used to explain such result. According to the theory, people who are more concerned about the environment have stronger intentions to behave pro-environmentally. Since they are more willing to behave appropriately, they are also more likely to act environmentally friendly.

People who believe the UK will be affected by climate change in the coming 30 years are greener behaved than those who do not believe. It is also true for those who believe the UK will be affected in the next 30 years and 200 years. However, those who believe the UK will only be affected in the next 200 years are not significantly different to those who do not

believe in the effect of climate change in the UK in the next 30 and next 200 years. This finding shows, as would be expected, that people who believe climate change is an urgent problem tends to behave more environmentally friendly. This can be explained by the NAM which proposes that pro-environmental behaviours actions are activated by the awareness of problem and how the problem could affect the world. As they have more awareness of the potential problem that arises from climate change, it is expected that they are more likely to engage in behaviours that can help to relieve the problem.

Surprisingly, people who disagree green is an alternative living style have a higher proenvironmental behaviour score than those who agree. However, people who engage in a green living style would not think that their original way of living style is an alternative as they are already used to it. Only people who do not have a green living would think that green is an alternative style of living. This explanation is also consistent with the finding which shows people who would like to do a lot more on the environment are more proenvironmentally behaved.

2.4.3.2 Significant Household-level Variables

The following paragraphs discuss the effects of household-level explanatory variables on individuals' pro-environmental behaviours.

Household Sociodemographics

Car ownership is a very significant explanatory household variable on individuals' proenvironmental behaviours. Individuals from households without a car are more environmentally friendly than those with a car, in which they are on average 3.75 points higher on the pro-environmental score. Car ownership can be considered as a barrier or a constraint for behaving pro-environmentally, especially in behaviours related to daily travels. As demonstrated by Tanner (1999), car ownership encourages people to drive and hence households with cars are less likely to engage in environmentally friendly commute methods. Therefore, it is not surprising that our result shows individuals from households that do not own a car are more environmentally friendly in their behaviours, as the pro-environmental score also consists of transport choice behaviours.

Household Structure

This study demonstrates a consistent result with previous findings (for example, Büchs and Schnepf, 2013; Longhi, 2013) that the presence of children in the households tends to reduce the individuals' pro-environmental behaviours. Individuals from single households are significantly different from those who are from households with more than one adult household members or children. In general, individuals living only with children are 0.67

points lower on their pro-environmental score while those living in non-single household are 0.25 points (non-single household with children) and 0.39 points (non-single household without children) lower on the pro-environmental score compared with people who live alone. Moreover, children's age is also important in explaining individuals' pro-environmental behaviours. Significant differences exist in households with children below two-year-old and children between five and eleven-year-old. The possible explanation is that a young child is a constraint for parents and other household members to have a green lifestyle.

Accommodation Characteristics

Tenure type and dwelling type are both significant in explaining individuals' proenvironmental behaviours. People living in home-owned with mortgage, social rented and privately rented accommodations are less likely to engage in pro-environmental behaviours than the homeowners. Meanwhile, people living in semi-detached houses, end-terraced houses and flats tend to participate in behaviours that benefit the environment more than those living in detached houses. Previous studies have suggested that tenure type and dwelling type are two major factors that affect the energy performance of the dwellings (Utley and Shorrock, 2006; Druckman and Jackson, 2008). Therefore, our results can be explained by the energy performance of the dwelling indirectly through the tenure and dwelling types. As efficient energy performance has a negative correlation with energy use, the more efficient the dwelling energy performance is, the less energy that needs to be consumed.

Neighbourhood Characteristics

Gifford and Nilsson (2014) suggest that people living near to a problem site tend to be more concerned about the environmental problems. Not surprisingly, the finding from this study also shows that people living in area with trash, litter or junk in the neighbouring streets tend to engage more in pro-environmental behaviours. However, it should be noted that such an effect is not as significant as other variables that have been discussed here. It may be because the poor environment situation acts as an appropriate threat to the people living around so that they become more responsive to behaviours that can benefit the environment (Hartmann *et al.*, 2015).

Residential area

People who are living in the East of England, London, South East and South West are more likely to participate in pro-environmental behaviours than the residents from the North East. It seems that there is a North-South difference in pro-environmental behaviours in England.

Moreover, people from Wales are also more likely to behave environmentally friendly than those from the North East. Nevertheless, people from Northern Ireland are less likely to engage in behaviours that benefit the environment.

There is also a rural-urban difference in the participation in environmentally friendly behaviours. People from rural areas tend to behave less environmentally friendly than those from urban areas, and this may be explained by the facts that there are more constraints in rural areas compared to urban areas.

2.4.3.3 Insignificant Individual-level and Household-level Variables

Marital status, religion and interviewers' observation on whether there is heavy traffic in the neighbourhood are found to be insignificant in explaining individuals' pro-environmental. Therefore, these variables have been excluded from the final model.

Marital status is significant until household-level fixed effect variables are added into the model. It is believed that the household level variables cancel out the effect of marital status as the household structure variable has more power in explaining individual-level behaviours. It is not the martial status that influence how people behave, but the household structure (whether the household is a single household or if children are present) that matters.

Religious belief do not have any significant effect in explaining the differences in proenvironmental behaviours although previous studies (for example, Pepper, Jackson and Uzzell, 2011; Hope and Jones, 2014) have demonstrated such an effect. However, as discussed by Gifford and Nilsson (2014), importance of religion in studying green behaviours remains inconsistent. Therefore, it is not too surprising that we cannot find any relationship between religion and environmentally friendly behaviours.

Neighbourhood characteristics are believed to have impacts on individuals' proenvironmental behaviours (Gifford and Nilsson, 2014). However, unlike the cleanliness of the neighbourhood which has an influence on the individuals' behaviour, traffic congestion problem is found to be insignificant.

Based on considerations about theoretical concepts, a range of interaction terms have been explored. These interactions include both same-level interactions (highest education level with individual monthly income, urban area with ownership of car, urban area with government office regions, and urban area with neighbourhood characteristics) and cross-level interactions (government office regions with education level, government office regions with ethnicity). However, these interaction terms either do not reduce the DIC statistics or they are insignificant at the 5% level. Therefore, no interaction term is included.

2.5 Further Exploration of the Household's Effects on Individual's Pro-Environmental Behaviours

In the UKHLS, a household is defined as a person or a group of people who share at least one meal a day **or** share the living accommodation which is their only or main residence (Lynn, 2009). Findings from this study demonstrate that pro-environmental behaviours for those who live in the same household are likely to be influenced by the features of the household and other household members. Due to these household effects, people's environmental behaviours in the same household are more alike than the behaviours for people from a different household.

However, we may wish to distinguish single- from multiple-persons households. In the analysis sample, there are around 15% of the respondents who live alone in single households while the remaining 85% are living in non-single (multi-person) households. In the analysis sample, we include those who live in single households even though there is only one person in each household. This is because we can borrow the strength of these single household characteristics to estimate the fixed effects (Rice *et al.*, 1998). As presented in the results and discussion section, 30.4% of the variation in the environmental behaviours is attributed to the differences between household (see Table 2-6). Moreover, the inclusion of household-level variables in the model also substantially reduces the household random effect variance. This indicates that these household-level variables (such as household structure and composition) are influential in explaining individual's environmental behaviours.

Nevertheless, some may argue that a household effect does not exist in single households as they contain only one person and that such cases are not helpful when estimating the household level random effects. Therefore, to better understand the estimation of household effects, the final cross-classified model is fitted separately to the two sub-samples, including individual, household, interviewer and area effects. The first sub-sample consists of 5,135 individuals from single households and the second sub-sample consists of 31,035 individuals from 17,438 non-single households. The two models are presented in Table A.7 and the corresponding random effects are summarised in Table 2-11. In the non-single household sub-sample, 30.3% of the variation in the environmental behaviours is at the household-level, i.e. the VPC in the non-single household sub-sample is approximately the same as the VPC in the final model of the full sample. When estimating the single-household sub-sample, the individual-level random effect is marginally significant but the household-level random effect is not (which is to be expected since individual and household effects are the same in this sub-sample). neither the individual- nor the household-level random effects are significant.

Table 2-11 Variances for the Final Cross-Classified Multilevel Models – A Comparison of Single and Non-Single Households

	Full Sample (N = 36,170)		Ü	ousehold 5,135)	Non-Single Household		
					•	035 from ouseholds)	
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	
Individual	20.443	(0.243)***	23.513	(11.924)*	20.392	(0.245)***	
Household	10.129	(0.292)***	7.390	(11.964)	10.045	(0.307)***	
Interviewer	2.094	(0.177)***	2.193	(0.369)***	2.061	(0.183)***	
Area	0.660	(0.129)***	0.272	(0.360)	0.680	(0.156)***	

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

Furthermore, the results from the two models (see Table A.7 in Appendix A) demonstrate that people who are living alone and those who are living in a shared household behave differently in pro-environmental behaviours. It is arguable that the changes in significance levels of the variables may be due to the sample sizes and the possibility of selection effects. It is possible that people who are more environmentally friendly choose to live alone rather than the other way round. However, it is still reasonable to conclude that household plays an important role in explaining individuals' behaviours.

Single householders, in general, are more environmentally friendly than their counterparts. As illustrated in Figures 2-3 to 2-8, they have stronger personal values and attitudes on environmental issues than non-single householders. This may explain how values and attitudes can be easily weakened by people who are living together. In particular, there is only a significant difference between those who are very interested and those who are not at all interested in politics in pro-environmental behaviours among single householders. Meanwhile, among those who are living in shared households, significant differences are observed between all levels of interest in politics and the reference group (very interested).

Notwithstanding the emphasis on personal values and attitudes, sociodemographic variables also explain the differences between those who are living alone and those who are living with others. For example, ethnicity becomes insignificant when the sub-sample consists of single household individuals while the ethnicity differences in environmentally friendly behaviours among those from non-single households remain significant. Furthermore, the North-South and urban-rural differences in behaving green diminishes among the single-householders.

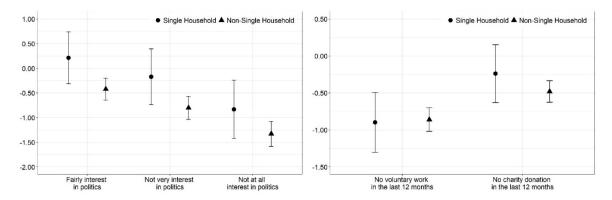


Figure 2-3 Estimates and 95% Confidence Intervals for the Level of Interest in Politics

Figure 2-4 Estimates and 95% Confidence Intervals for Autistic Acts

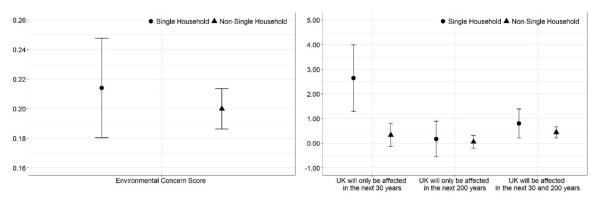


Figure 2-5 Estimates and 95% Confidence Intervals for Environmental Concern Score

Figure 2-6 Estimates and 95% Confidence Intervals for the Awareness of Effect of Climate Change in UK

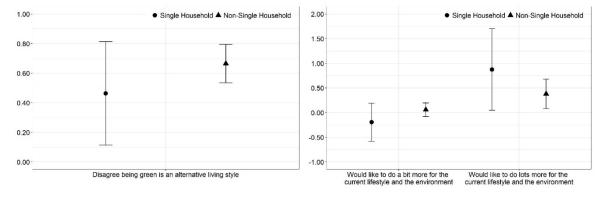


Figure 2-7 Estimates and 95% Confidence Intervals for Disagreeing Being Green is an Alternative

Figure 2-8 Estimates and 95% Confidence Intervals for Thoughts about Current Lifestyle and the Environment

2.6 Further Exploration of the Potential Impact of the Lack of Weights in the Analysis

It is recommended by the UKHLS committee that sampling weights should be considered when analysing the UKHLS data (Lynn and Kaminska, 2010; Knies, 2014). However, due to the fact that MLwiN does not support the use of weights in MCMC estimation, sampling weights are not used in this study. Instead of employing a design-based approach analysis where weights are used, this study adopts a model-based approach, where the variables used to derive the weights are included in the modelling.

In order to examine the potential impact of the lack of weights in the analysis, we conduct a sensitivity analysis. The sensitivity analysis evaluates whether the results from unweighted and weighted analysis are sensitive to the use of sampling weights. The MLwiN allows the inclusion of weights for the IGLS estimation procedure. Hence, two separate 2-level (individual- and household-levels) linear models are fitted to the data using IGLS estimation. The first model does not include the sampling weights (but includes the variables involved in weighting in the model) while the second model applies sampling weights at both levels (individual and household) in the analysis. The two models are presented in Table A.8 in the Appendix A. The results show that the coefficients in the weighted analysis are the same as those in the unweighted analysis. There are no differences between estimates in both fixed and random effects across the two models. However, there is a slight difference in the standard errors between the unweighted and weighted models, in that they are slightly higher in the weighted analysis than those in the unweighted analysis.

Based on the sensitivity analysis, it can be concluded that the lack of sampling weights in the analysis does not have any substantial effect on the results. It also confirms that including design variables in the unweighted analysis is as effective as a design-based approach where weights are applied (Snijders and Bosker, 2012). Therefore, the findings from this study are robust and generalisable.

2.7 Limitations

The final model presented in Chapter 2.4 demonstrates how the differences between household, interviewer and area explain individual environmental behaviours. However, the data from the Wave 4 of the UKHLS have imposed some limitations on the estimations of these effects. The following section will discuss these limitations with a special focus on how household, interviewer and area effects are operationalised using the Wave 4 UKHLS data.

Due to nonresponses, single householders and other reasons, there are 11,654 respondents (32.2% of the analysis sample) who live in households in which they are the only respondent (single-respondent household). The remaining 24,516 respondents (67.8% of the analysis sample) live in multiple-respondent households. In the final model, individuals from both single-respondent households and multiple-respondent households are included in the analysis. As discussed in previous sections, retaining households with only one respondent in the analysis allows them to contribute to the fixed effects estimation (Rice et al., 1998). Furthermore, Bell, Ferron and Kromrey (2008) provide evidence from their simulation study that the proportion of one-respondent household had an insignificant impact on model estimation when there are large number of level-2 clusters. A more recent study from Bruyndonckx, Hens and Aerts (2018) also demonstrates similar conclusions. They also suggest that removing single-respondent households from the analysis can even lead to biased results. Similar to the problem arising from individuals who live in single households, the individual and household random effects in single-respondent households cannot be distinguished. We therefore divide the final analysis sample into two sub-samples. The first sub-sample contains individuals who live in single-respondent households (N = 11,654) while the second sub-sample contains those who live in multiple-respondent households (N = 24,516). The final cross-classified model is fitted separately to the sub-samples. The random effects are summarised in Table 2-12. As shown in Table 2-12, both individual- and household-level random effects are not significant when we examine the single-respondent household sample and allow for both effects in the model. For the multiple-respondent household sample, the two effects are both significant and, importantly, the results are very similar to the full sample. Therefore, there is strong evidence that individual and household effects are important in explaining individual environmental behaviours.

Table 2-12 Variances for the Final Cross-Classified Multilevel Models – A Comparison of Single-Respondent and Multiple-Respondent Households

	Full Sample (N = 36,170)		_	espondent sehold	Multiple-Respondent Household		
	•	, ,	(N = 1	1,654)	• .	516 from ouseholds)	
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	
Individual	20.443	(0.243)***	13.789	(12.322)	20.153	(0.247)***	
Household	10.129	(0.292)***	17.387	(12.333)	9.927	(0.336)***	
Interviewer	2.094	(0.177)***	2.438	(0.263)***	1.863	(0.190)***	
Area	0.660	(0.129)***	0.745	(0.309)***	0.574	(0.197)***	

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

In the final sample, 6.6% of the respondents (N = 2,398) live in Northern Ireland whereas the remaining 93.4% (N = 33,772) live in England, Wales and Scotland. As described in the data section (Chapter 2.2.2), the Northern Ireland employed a different sampling design compared to the rest of the UK. In Northern Ireland, an unclustered single-stage design was used to select addresses. Therefore, households are nested within interviewers only. Unlike the sample for England, Wales and Scotland, the cross-classified structure between interviewers and areas is absence in the Northern Ireland sample. The analysis sample of the Northern Ireland consists of 2,398 individuals from 1,492 households and interviewed by 67 interviewers. In order to examine the differences between Northern Ireland and the rest of the UK, we fit the final cross-classified model to the Northern Ireland sample (N = 2,398) and the to the England, Wales and Scotland sample (N = 33,772) separately. The fixed effects of the two models are presented in Table A.9 in the Appendix A, while the corresponding random effects are summarised in Table 2-13. Unsurprisingly, the area-level random effect is not significant in the Northern Ireland sample, yet it remains significant in the sample of England, Wales and Scotland. It should be noted that due to the absence of the area-level in the Northern Ireland sample, only individual-, household- and interviewer-level random effects are successfully identified in this region. The random effects estimates for the England, Wales and Scotland sample are all significant and very similar to the estimates obtained from the full sample. We conclude, that both interviewer and area effects play a crucial role in explaining individual environmental behaviours.

Table 2-13 Variances for the Final Cross-Classified Multilevel Models – A Comparison of the Northern Ireland Sample and the England, Wales and Scotland Sample

	Full Sample		Northern Ireland Sample		England, Wales and Scotland Sample	
	(N = 36,170)		(N = 2,398)		(N = 33,372)	
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)
Individual	20.443	(0.243)***	19.769	(0.920)***	20.487	(0.253)***
Household	10.129	(0.292)***	5.767	(2.414)**	10.254	(0.303)***
Interviewer	2.094	(0.177)***	2.436	(0.744)***	2.058	(0.181)***
Area	0.660	(0.129)***	2.592	(2.191)	0.658	(0.129)***

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

2.8 Conclusion

This paper explores the role of households in individuals' pro-environmental behaviours using a cross-classified multilevel modelling approach to account for the cross-classified structure of interviewer and area effects. Other studies on individuals' environmentally friendly behaviours are limited to single level analysis and interviewer and area effects have not been taken into account. The adoption of multilevel modelling in analysing individuals'

pro-environmental behaviours allows the household effect to be distinguished from the individual effect. Furthermore, the cross-classified specification is considered to account for the interviewer and area effects on the outcome of interest.

The random specification in the final model identifies the household effect on individuals' environmentally friendly behaviours, as well as the interviewer and area effects. After controlling for the household effect, both interviewer and area effects are significant, resulting in the cross-classified two-level multilevel model. The significance of the cross-classified structure suggests that the interviewer allocation in the survey implementation may have allowed sufficient penetration to separate the interviewer and area effects. This further suggests that when asking respondents how often they undertake a particular behaviour in a face-to-face survey interview, researchers should be aware of the potential of interviewer effect on the response, especially in designing questions related to pro-social behaviours.

The role of household in individuals' environmentally responsible behaviours are found to be significant. The household-level random effect contributes to 30% of the total variation among individuals when all the fixed effect parameters are taken into consideration. Both individual- and household-level variables reduce the household variance. However, it is surprising to find that the inclusion of individual-level variables substantially reduces the household random effect variance. It is hypothesised that individual-level effects may be aggregated as household-level effects. The results from the sub-analyses demonstrate that individuals from the same household share similar sociodemographic characteristics and personal values. Such findings have supported the hypothesis and explained why the individual-level variables manage to reduce the household random effect. Meanwhile, the household's role is further explored by fitting the full model to individuals from single households and individuals living in non-single households. Despite the sample size and the possibility of selection effects, people who are living alone are more environmentally concerned than their counterparts.

Based on the established theoretical frameworks and psychological theories, explanatory variables are selected to explain individuals' pro-environmental behaviours and the results support these theories. The results from the final model confirm these theoretical frameworks and previous findings on the relationship between pro-environmental behaviours and individual sociodemographics, personal values, environmental concerns and attitudes, household sociodemographics, household structure, accommodation characteristics, neighbourhood characteristics and residential areas. Older people, women, full-time students, retired people, higher educated people, immigrants and higher individual income individuals are more likely to behave environmentally friendly. Moreover, those who

are more interested in politics, have involvement in voluntary works and contribution to charity donations tend to engage in environmentally responsible behaviours. Also, the supporters of the Liberal Democrat, Green Party and Alliance Party act greener than those that support the Conservative Party and this finding is consistent with the results in the United States. Unsurprisingly, environmental concern and the level of awareness of the severe consequences of climate change are positively correlated with how the individuals behave.

At household level, ownership of car may hinder household members to use green transportations as it is more convenient for them to use the car rather than cycling, using public transports or walking. People who are living alone are found to behave differently from those living with other household members. Meanwhile, for households with children, the age of the children also explains the environmental behaviours of the adult household members. People living with children below two years old and between five to eleven years old are less likely to engage in pro-environmental behaviour. Individuals living in homes owned outright and living in semi-detached houses, end-terraced houses, flats and bungalows are more likely to participate in environmentally responsible behaviours. This may be because these dwelling and tenure types have a better energy efficiency measure installed and more efficient energy performance, resulting in less heating required. Poor environment increases the awareness of an environmental problem; people are more likely to engage in environmentally responsible behaviours if they live in an area with a lot of trash and rubbish on the street. Finally, the results demonstrate a North-South and rural-urban difference in pro-environmental behaviours. People living in the south and urban areas are found to behave more environmentally friendly.

To summarise, the results from this paper provide evidence that household plays an important role in individuals' daily pro-environmental behaviours. Government policies should not only promote green behaviours among individuals, but also encourage environmentally responsible behaviours by targeting different types of households, as different household types are found to be behaving differently.

There are limitations in this study. Firstly, measurement errors are likely to exist in the outcome of interest. In the UKHLS, self-measured behaviours are obtained through a face-to-face survey interview. Respondents are asked to judge how often they engage or participate in the eleven behaviours. However, such as approach is subject to response bias and measurement errors (Steg, van de Berg and de Groot, 2012). It is suggested that interviewers' sociodemographics, the way how they administer the survey interviews, the intonation in delivering the words during interviewers and the reaction to respondents' difficulties with the questionnaires are able to induce measurement errors in survey interviews (Groves,

1989). For example, a finding from Bateman and Mawby (2004) shows that respondents are more willing to pay for an environmental good if they are interviewed by better-dressed interviewers. Furthermore, the Social Attribution Model and Conditional Social Attribution Model (Fendrich *et al.*, 1999; Johnson *et al.*, 2000) also provide explanations on how respondents tailor their responses to interviewers based on the norms, values and beliefs and how characteristics of the respondents interact with the interviewers. These models may be able to explain why the interviewer random effect is significant in the final model. Currently, information of the interviewer is only available for Wave 1 of the UKHLS. Since interviewers have changed significantly between the first and the fourth waves, further investigation is not possible as no information is available for Wave 4 of the UKHLS.

Secondly, the UKHLS is not designed to only measure pro-environmental behaviours, as a consequence, some explanatory variables that have been found to be significant in previous research are not included in the survey and are hence not available in the dataset for analysis. For instance, the New Ecological Paradigm Scale (NEP; Dunlap and Van Liere, 1978) or the New Ecological Paradigm Scale-Revised (NEP-R; Dunlap *et al.*, 2000) are two established and well-validated scales that are used to measure people's environmental concern. The NEP-R, in particular, is used in much previous research that investigates pro-environmental behaviours at individual and household levels and has been found to be very efficient in explaining environmental-related behaviours (for example, Barr, 2007; Fielding, McDonald and Louis, 2008; Whitmarsh and O'Neill, 2010). Such information could help to increase the explaining power of the current model.

Thirdly, the outcome of interest is aggregated based on eleven items. In this case, all the behaviours are aggregated into one score. However, different green behaviours are not necessarily correlated and behaviours may be encouraged or discouraged differently (Steg, van de Berg and de Groot, 2012). Lynn (2014) identifies three different dimensions in these eleven items using data from Wave 1 of the UKHLS, namely the home-, transport- and purchasing-related behaviours. Moreover, findings also show that people who are more environmentally friendly in home- and purchasing-related behaviours do not necessarily behave greener in transport-related behaviours (Lynn, 2014). This study only focuses on the general behaviours, but it ignores the differences and inter-correlations between the three dimensions. Therefore, the next stage of research will examine these three types of behaviours separately.

Chapter 3: Identifying Household Effects on Individuals' Transport-, Home- and Purchasing-related Environmental Behaviours using a Multilevel Modelling Approach (Paper 2)

3.1 Introduction

The United Kingdom (UK) government has been monitoring the change in greenhouse gas (GHG) emission and its impacts on climate change since the sign up of the Kyoto Protocol in 1995. The recent signing up of the Paris Agreement on Climate Change by the European Union further increases the government's momentum to reduce emissions. Human activities are found to be significant in the contribution of the emission of GHG. These activities are not only limited to business or industrial activities, but also include people's daily behaviours. According to the UK's Carbon Footprint Report by the Department for Environment, Food and Rural Affairs (2017), 17% of the UK consumption-related GHG emissions in 2012 was generated by residential dwellings directly. 38% was associated with local produced goods and services that are consumed by people living in the UK and the remaining 45% was produced by imported goods and services. In other words, the emissions of GHG are directly and indirectly influenced by people's behaviours.

Although the influence on the environment of each individuals' behaviours may be small and insignificant, cumulated individuals' behaviours can have an important impact on the environment, especially, when the UK is a nation with more than 65 million population. Understanding the daily behaviours of people, therefore, is key to the UK government to reduce GHG emissions at national level. By promoting more environmentally responsible behaviours among the public, the UK government would be able to reduce the emission of GHG directly and indirectly. For instance, the government requires large shops (including major supermarkets) in England to charge customers 5 pence for all single-use plastic bags since October 2015 (Department for Environment Food & Rural Affairs, 2015). It is expected that £13 million of carbon can be saved over the next ten years. To effectively encourage people to change their behaviours or adopt a greener living style through policy implementation, it is important to understand why individuals or households act in particular ways.

3.1.1 Background

Pro-environmental behaviours are behaviours that have positive impacts on the environment or behaviours that minimise harmful impacts on the environment. People do not necessarily need to be aware of the outcomes of their behaviours; it is the impacts of their actions on the environment that matter. These behaviours are referred to as impact-oriented behaviours (Stern, 2000). There are also behaviours that are intentionally acted to benefit the environment. These actions are based on the self-conscious decisions because action of people follows their desire to protect or improve the environment. Stern (2000) describes this type of behaviour as *intent-oriented* as it is the human intention that drives their action. Regardless of the differences between impact-oriented and intent-oriented behaviours, both of them attract a lot of attention from researchers. Although the research goals may be different for these two types of pro-environmental behaviours, they are widely studied by researchers to understand why an individual or a household engages in these behaviours. In this paper, both impact- and intent- oriented environmentally friendly behaviours are considered. We believe that people are self-conscious about their actions on some occasions, while their behaviours can also be habits or daily routines where they are not aware of the outcomes of their actions. Nevertheless, the outcomes for these behaviours are positive for the environment.

Environmental behaviours can be measured in different ways. Some studies examine the general environmental behaviours by using a unidimensional measure. In these studies, researchers use a single measure to quantify how green the people behave in their daily lives so that they are able to study a wide range of behaviours simultaneously. However, using a unidimensional measure may not be sufficient if we aim to explore the underlying determinants of environmentally friendly behaviours more comprehensively. Although Kaiser and Wilson (2004) demonstrate that a unidimensional measure does not show any statistical difference from multidimensional measures, measures of environmental behaviours are often treated as multidimensional. In particular, Steg, van de Berg and de Groot (2012) suggest that different pro-environmental behaviours are not necessarily correlated and in addition, behaviours can be influenced differently by different determinants. Therefore, some researchers narrow their research to specific behaviours so that they can identify and compare different factors that influence these behaviours. Moreover, analysis of combined or aggregated behaviours may also hide certain underlying trends and effects may be cancelled out when averaged. Evidence shows that participation in one green behaviour does not necessarily infer the same conclusion for another type of behaviours (for example, Thøgersen and Ölander, 2003; Lynn, 2014). Therefore,

multidimensional measures should be considered and analysed separately and jointly to better understand different types of environmental behaviours.

In environmental behaviour research, established sociological frameworks are often adopted to investigate how the external and internal factors influence people's environmental behaviours. Among all the commonly used theories and models, the Theory of Planned Behaviours (Ajzen, 1985;1991) and the Norm-Activation Model (Schwartz, 1977) are the two most influential frameworks in the area of study. These frameworks provide well-established constructs and definitions for researchers to identify the underlying socio-psycho factors that have impacts on people's environmentally friendly behaviours (Bamberg and Möser, 2007). The Theory of Planned Behaviours focuses on pro-self interest whereas the Norm-Activation Model stresses on the altruism nature of people (Schwartz, 1977; Ajzen, 1985;1991). Nevertheless, both of these frameworks have been proven to be success in explaining and predicting different types of pro-environmental behaviours (for example, Anable, 2005; Fielding, McDonald and Louis, 2008; De Groot and Steg, 2009; Lind *et al.*, 2015).

Regardless of the frameworks adopted in the studies, personal factors, contextual factors and environmental concerns and attitudes have been identified to have significant influences on individuals' pro-environmental behaviours. These factors have been well documented and reviewed in the literature (for example, Kollmuss and Agyeman, 2002; Barr, 2007; Longhi, 2013; Gifford and Nilsson, 2014). These reviews are mainly based on previous studies which investigate general pro-environmental behaviours or specific behaviours at individual level. A very comprehensive literature review is also documented in Chapter 1.

3.1.2 Aims and Methods

Lynn (2014) identifies three behaviour dimensions (transport-, home- and purchasing-related environmental behaviours from eleven daily pro-environmental behaviours using Wave 1 of Understanding Society, the UK Household Longitudinal Study. The research aims of this paper are: 1) to analyse these three different types of individuals' pro-environmental behaviours; 2) to identify the factors that influence these behaviours, especially the role of households in these behaviours; and 3) to investigate the interviewer and area effects on these behaviours using a multilevel modelling framework.

This paper extends previous analysis described in Chapter 2 that investigates general behaviours only. Analysing general behaviours may only allow a broad understanding of the different drivers behind individuals' overall environmental behaviours, but fails to account for the differences among different types of green behaviours. As discussed by Steg and Vlek (2009), different types of pro-environmental behaviours are not necessarily correlated.

Behaviours can be motivated and influenced by different factors; aggregated behaviours may hide certain underlying trends; and effects may also be cancelled out during aggregation. Therefore, it is essential to focus on specific types of behaviours. This paper adopts, similar to the previous chapter, various sociological and psychological approaches to explain the significant impacts of both individual and household characteristics on the three behaviours. Since attitudes can influence behaviours and this causal direction can also be reversed, we assume attitudes affect behaviours in this study.

The analysis is conducted using Wave 4 of Understanding Society, the UK Household Longitudinal Study (UKHLS). The dataset contains rich information on sociodemographics, personal values and other details at both individual and household levels. Respondents are asked to provide detailed information on their daily environmental behaviours and they are also invited to complete a self-completion questionnaire about their environmental attitudes. This dataset is unique compared to other national surveys in the UK as it contains not only individual or household sociodemographic information, but also self-reported behaviours and attitudes towards environmental issues.

In the UKHLS, individuals are nested within households. Due to the multi-stage survey design and the data collection procedure, households are further nested within a cross-classified structure between interviewers and geographical areas. As people living in a nearby area tend to behave similarly and respondents interviewed by the same interviewer may also be influenced by the interviewer in a similar way, we hypothesise that both interviewers and areas impact on individuals' responses. Therefore, in order to account for the possible interviewer and area effects adequately, the cross-classification between interviewers and areas is included in the model by using a cross-classified multilevel model.

This paper consists of four main sections. The data section summarises the details of the dataset that is used in the analysis. The methodology section discusses the modelling approach and the justifications of the method. The results and discussion section presents the findings and interprets the final models. Finally, the paper ends with a conclusion and recommendations for further research.

3.2 Data

3.2.1 Overview

This study uses data from Wave 4 of Understanding Society, the UK Household Longitudinal Study. It is a representative national panel study in the UK with samples covering England, Scotland, Wales and Northern Ireland. This survey contains information at both individual

and household levels. Additional modules are also included at different waves to collect data and opinions relating to different topics. In particular, Wave 4 of this study contains an environmental behaviour module and an environmental attitudes module. These two environmental-related modules collect information about individuals' environmental behaviours and attitudes. The details of the survey design, data collection procedure, interviewer allocation and data structure are described in Chapter 2.

3.2.2 Analysis Sample

The dataset consists of three sample components (i.e., General Population Sample, Ethnic Minority Boost Sample and the former British Household Panel Survey) and contains information from 45,157 individuals from 25,831 households. Individuals whose information is obtained from proxy interview (3,940 cases), those who do not complete the selfcompletion questionnaire (8,205 cases) and cases with missing information on government office region (29 cases) are removed from the dataset. Therefore, the full sample contains data from 38,927 individuals from 23,818 households, who are interviewed by 637 interviewers living in 6,400 primary sampling units (PSUs). Cases with missing outcome variables are removed from the dataset and the remaining sample is referred to as the initial analysis sample (see Table 3-1). Since there are item nonresponses in some of the potential categorical variables, an additional category "missing" is included in these variables to retain a constant analysis sample size for the whole modelling processes. Finally, cases with missing continuous explanatory variables are listwise deleted from the dataset. The final analysis sample is summarised in Table 3-1. The distributions of respondents per household, the number of interviewers per area and areas per interviewers for the three outcomes based on the corresponding full samples are presented in Tables B.1, B.2 and B.3 of Appendix B. Moreover, the descriptive statistics of the final analysis sample datasets by potential explanatory variables are included in the Tables B.4 and B.5 of Appendix B.

Table 3-1 Analysis Samples for the Three Outcomes: Transport-, Home- and Purchasingrelated Pro-Environmental Behaviours

	Initia	l Analysis :	Sample	Final Analysis Sample				
	Transport	Home	Purchasing	Transport	Home	Purchasing		
Individual	32,538	38,811	37,156	32,322	38,509	36,896		
Household	20,552	23,777	23,419	20,464	23,645	23,298		
PSU	5,896	6,394	6,328	5,865	6,356	6,291		
Interviewer	632	637	636	632	637	636		

3.2.3 Outcome Variables

The three outcome variables to be considered are transport-related, purchasing-related and home-related pro-environmental behaviours, which are identified by Lynn (2014) using Wave 1 of the UKHLS data. He performs an exploratory factor analysis on the questions from the environmental behaviour module and successfully identifies three behavioural domains from these eleven pro-environmental behaviours (see Table 3-2). First, the same analysis is replicated here on a random sample of Wave 4 data (N = 21,283) to investigate if any change has occurred since Wave 1 in the broad categorisation of environmental behaviours. Results show that the domains that are previously identified are also applicable in the Wave 4 data and this study. Secondly, a confirmatory factor analysis is performed on another distinct random sample (N = 21,283) to examine the construct validity of the eleven items.

Explanatory Factor Analysis

Explanatory factor analysis (EFA) is used here to identify domains (or dimensions) of proenvironmental behaviours from eleven behaviours that are included in the environmental behaviour module. EFA is an exploratory technique to determine the common latent factors and it is often used in the early stage of scale development and construct validation (Brown, 2015). Previously in the working paper in Chapter 2, we have analysed the overall behaviours by summarising all the behaviours as a unidimensional index. Here, we are interested in decomposing the unidimensional index into multidimensional indexes for further investigation.

EFA is performed on the eleven items from the environmental behaviour module that are listed in Table 3-2 using STATA 14.0 (StataCorp, 2013). In the face-to-face interview, respondents are asked to report how often they are engaged in these behaviours. Possible answers are "always", "very often", "quite often", "not very often", "never" and "not applicable, cannot do this". Prior to the factor analysis, some responses to the eleven items are reversed-coded, so that a large value indicates that the behaviour is performed more often.

Table 3-2 List of Pro-Environmental Behaviours in Wave 4 of the UKHLS

- **1** Leave your TV on standby for the night (tv)
- **2** Switch off lights in rooms that aren't being used *(light)*
- 3 Keep the tap running while you brush your teeth (water)
- **4** Put more clothes on when you feel cold rather than putting the heating on or turning it up *(heat)*
- 5 Decide not to buy something because you feel it has too much packaging (packaging)
- **6** Buy recycled paper products such as toilet paper or tissues (*products*)
- 7 Take your own shopping bags when shopping (bags)
- **8** Use public transport (e.g. bus, train) rather than travel by car (pubic transport)
- **9** Walk or cycle for short journeys less than 2 or 3 miles (walk)
- **10** Car share with others who need to make a similar journey (*car*)
- **11** Take fewer flights when possible (*fly*)

The results of the EFA are presented in Table 3-3, suggesting that three significant factors can be identified from the eleven pro-environmental behaviour items. Factor 1 distinguishes transport-related behaviours (use public transport, walk or cycle, car share and take fewer flights) from the other seven items. Factor 2 identifies the remaining five behaviours at home (leave TV standby, switch off lights, keep water running, put on clothes rather than turn up the heating and take shopping bag). Finally, factor 3 is identified by contrasting purchasing-related behaviours (avoid excess packaging and buy recycled paper products) with the other behaviours. The analysis result is consistent with the EFA results performed on the first wave of the UKHLS by Lynn (2014).

Confirmatory Factor Analysis

After identifying the three different factors from the eleven behaviours, confirmatory factor analysis (CFA) is conducted to further examine the construct validity. Unlike EFA that identifies underlying factors, CFA is used as a tool to verify the hypotheses about observed items and the latent constructs (Skrondal and Rabe-Hesketh, 2004). The difference between EFA and CFA is that the former one is data-driven while the latter is theory-driven. CFA is a common statistical technique in social science for scale and construct validation and it is often used after EFA (Brown, 2015). It has become a standard procedure for scale development in psychological research (Gallagher and Brown, 2013).

Based on the working paper from Lynn (2014) and the results from the EFA in this paper, an eleven-item, three-dimensional confirmatory factor model (Transport, Purchasing and Home) is estimated using STATA 14.0 (StataCorp, 2013) and the results are shown in Table 3-3. The goodness-of-fits statistics demonstrate a good model fit: $\chi^2(41) = 1259.493$, p=0.000; CFI = 0.923; SRMR = 0.025 and RMSEA = 0.037 (Hu and Bentler, 1999; Fan and Sivo, 2005). We do not consider the chi-square test for model fit as in large sample significant results are always

obtained. All the standardised factor loadings (right column of Table 3-3) are statistically significant at the 1% level. Although the magnitudes of the factor loadings range between 0.21 and 0.64, given the scale has only eleven items and it contains three dimensions, the result is marginally acceptable. Therefore, we can confirm that the three dimensions identified by Lynn (2014) and the EFA are able to reflect the underlying latent constructs of the eleven items.

Table 3-3 Factor Loadings of the Eleven Pro-Environmental Behaviour Items

	Explanatory Factor Analysis	Confirmatory Factor Analysis
Transport		
Item 8 (public transport)	0.664	0.639
Item 9 (walk)	0.590	0.576
Item 10 (car)	0.620	0.541
Item 11 (fly)	0.403	0.340
Home		
Item 1 (<i>tv</i>)	0.198	0.207
Item 2 (light)	0.457	0.289
Item 3 (water)	0.294	0.322
Item 4 (heat)	0.271	0.347
Item 7 (bags)	0.242	0.442
Purchasing		
Item 5 (packaging)	0.582	0.541
Item 6 (products)	0.634	0.564

Derivation of Outcome Variables

Responses of the eleven items listed in Table 3-2 are first recoded to range between zero and four, where four indicates the individuals always engage in the behaviour and zero indicates they never engage. The response "not applicable, cannot do this" is coded as missing. The three response variables are three indexes that are further derived from the corresponding raw scores.

It is a common method in the literature to use each item's factor loading as the corresponding weight to calculate the weighted sum score for each factor dimension, but summing up the individual items by factor to obtain the sum score is usually easier to interpret and understand. Lynn (2014) compares the weighted sum score with the unweighted sum score of the overall index of environmental behaviours and the results show that there is no significant difference between these two scores. Therefore, the unweighted sum score approach is used here to calculate the raw score of the three outcome variables.

The raw score of transport-related behaviours is the sum of items 8, 9, 10 and 11, ranging from zero to 16. For respondents with less than or equal to 25% of item missing among these four items (i.e. maximum one item nonresponse), the average for the non-missing items is used to calculate the raw score. The raw score of home-related behaviours is the sum of the first four items and the seventh item. Similarly, the average for the non-missing items is used to calculate the raw score when there is a minimum of four out of the five items not missing. Items 5 and 6 add up to the raw score of purchasing-related behaviour. In order to compute the raw score, both items should be non-missing. The score ranges between zero and eight. A full description of missingness patterns of the relevant items for these three raw scores which are based on the full sample (N = 38,927) is shown in Table 3-4.

Table 3-4 Pattern of Missing Items for the Three Raw Scores

Number of	Tran	sport	Но	me	Purch	nasing
Missing	(4 it	ems)	(5 it	ems)	(2 it	ems)
	N	%	N	%	N	%
0	21,702	55.75	37,071	95.23	37,156	95.45
1	10,836	27.84	1,740	4.47	1,506	3.87
2	4,710	12.10	93	0.24	265	0.68
3	1,120	2.88	12	0.03	-	-
4	559	1.44	5	0.01	-	-
5	-	-	6	0.02	-	-
Total	38,927	100.00	38,927	100.00	38,927	100.00

Finally, the raw score is converted into a four-point-scale index, ranging between one and four, with higher values indicating more pro-environmentally behaved in the corresponding behavioural domains (i.e., 1 = very low level participation in the behaviour; 2 = low level participation; 3 = some participation; and 4 = high level participation). Frequencies (Table 3-5) and the bar charts of the distribution of the derived outcomes (Figure 3-1) are presented below. As shown in these figures, the indexes for transport-related and purchasing-related behaviours are positively skewed while the index of home-related behaviours is negatively skewed.

Table 3-5 Frequencies of the Three Outcomes: Transport-, Home- and Purchasing-related Pro-Environmental Behaviours

	Tran	sport	Но	me	Purchasing		
	N	%	N	%	N	%	
Very Low	13,425	41.54	1,366	3.55	16,124	43.70	
Low	12,890	39.88	8,234	21.38	12,897	34.96	
Some	5,086	15.74	17,472	45.37	6,029	16.34	
High	921	2.85	11437	29.70	1846	5.00	
Total	32,322	100.00	38,509	100.00	36,896	100.00	

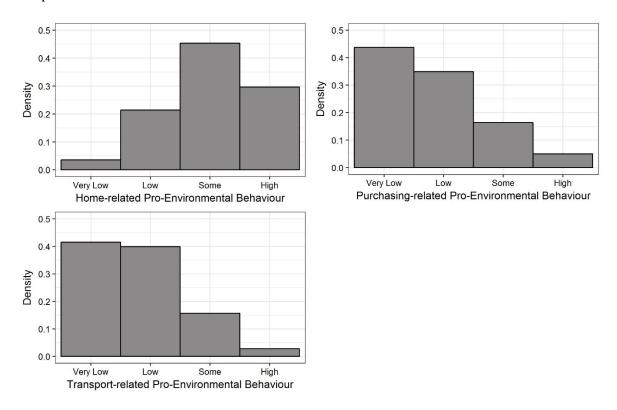


Figure 3-1 Distributions of the Home-, Transport, and Purchasing-related Pro-Environmental Behaviours

To further investigate whether or not the three outcomes are correlated with each other, the Spearman's rank order correlation (or the Spearman's rho correlation) is calculated. It is a non-parametric version of the Pearson's correlation and it can be used to test the association between two ordinal variables (Chen and Popovich, 2002). Table 3-6 presents the Spearman's rho correlations among the transport-, home- and purchasing-related behaviours. Weak but significant correlations are observed between the transport-related behaviours with the other two behaviours (home-related behaviours: ρ = 0.123; purchasing-related behaviours: ρ = 0.168). Meanwhile, there is a modest significant correlation between the home- and purchasing-related behaviours (ρ = 0.211). The findings are consistent with the results obtained by Lynn (2014). Although the author obtains the Pearson's correlation based on the three continuous raw scores, the correlations are very similar to the Spearman's rho correlation calculated from the three ordinal indexes. This further confirms that the three behaviours are not highly correlated with each other.

Table 3-6 Spearman's Rho Correlations between Three Pro-Environmental Behaviours

	Transport	Home	Purchasing
Transport	1.000		
Home	0.119	1.000	
Purchasing	0.169	0.211	1.000

Note: all correlations are statistically significantly at 1%.

3.3 Methodology

3.3.1 A Hierarchical Generalised Linear Modelling Framework

In the UKHLS, eligible individuals from the same household are interviewed by the same interviewer and hence individuals are clustered within households. Meanwhile, the sampling design of the UKHLS also allows an interviewer to work in more than one PSU and there is more than one interviewer working in each PSU, resulting in a cross-classified structure between the interviewers and geographical areas. As individuals from the same household may share some similarities (for example they share the same household characteristics and settings), individuals cannot be assumed to be independent. The violation of independence of observation leads to underestimation of standard errors and hence provides wrong statistical inferences (Snijders and Bosker, 2012). Therefore, special statistical techniques have been developed to analyse this type of hierarchical data.

There are several possibilities to analyse clustered data. One of the common methods is to apply robust standard error estimation (Goldstein, 2011). This approach allows less dependence on the assumption of the distribution by modifying the standard error and the confidence interval estimates. Moreover, it is very common to aggregate the lower-level data to the higher-level in social research (Hox, 2010). By aggregating the lower-level data, we focus on the averaged higher-level units. However, aggregation may result in potential errors. Lower-level variables that are aggregated become higher-level variables rather than containing information directly to the lower-level units. Furthermore, aggregation may also lead to the 'ecological fallacy' (Robinson, 1950). As relationships between lower-level units can be different from the relationships between higher-level units, it is not possible to use the higher-level relationship to infer the lower-level one.

On the other hand, multilevel modelling is a disaggregated approach that is popular in analysing data with complex structures. It works well on clustered data as it accounts for the complicated hierarchical structure and it focuses on the variability that is associated with each level of nesting (Hox, 2010; Goldstein, 2011). Multilevel analysis allows the residual variances to be partitioned into different components. In our case, the residual variation can be partitioned into within-individuals, between households, between interviewers and between geographical areas (Goldstein, 2011). As one of our main interests is to investigate the effects of household, interviewer and area on individuals' pro-environmental behaviours, multilevel modelling is used for analysing the data in this paper.

Individuals' behaviours may not only be influenced by other household members or the household settings, but also by other higher-level units (i.e., the geographical areas and

interviewers). The findings from Chapter 2 supports the assumption that some variations in behaviours are due to the area difference. Furthermore, interviewers may also induce measurement errors on the response (Groves, 1989). Measurement error (or observation error) occurs when there is a difference between the actual and the reported answers (Groves, 1989). The sociodemographics, attitudes and outlooks of the interviewers can lead to potential measurement errors on survey responses (Groves, 1989; Hox, de Leeuw and Kreft, 1991). Evidence from Chapter 2 also shows that part of the variations in the reported pro-environmental behaviours can be explained by the interviewers. As discussed previously, the hierarchical structure of the data are not completely perfect as interviewers are not fully nested within PSUs. In order to incorporate the cross-classified structure in the analysis to allow a lower-level unit (i.e., households) to be classified in more than one higher-level (i.e., interviewers and PSUs), multilevel cross-classified model can be used (Goldstein, 2011). This is a widely adopted approach to study and partition the effects on Interviewers and PSUs in survey nonresponse (Campanelli and O'Muircheartaigh, 1999; Vassallo et al., 2015). It is also used to distinguish the Interviewer and PSU effects that can explain the individuals' variation in pro-environmental behaviours in Chapter 2.

In this paper, the three outcome variables are ordered categorical responses with four categories and they are all skewed (see Figure 3-1 in Section 3.2). Ordered categorical data are often treated as continuous data in social science research. However, such an approach is problematic as it can lead to bias (Hox, 2010). It has been demonstrated that if there are four or fewer categories or if the distribution is skewed, the estimates and their standard errors will have a severe downward bias (Hox, 2010). In order to adjust for the possible bias, generalised linear models can be used as they are designed especially for this type of ordered categorical data. Particularly suitable are the cumulative ordered logit models. Goldstein (2011) further extends the model to situations where the ordered responses are hierarchical in nature. Therefore, rather than treating the ordered scale as continuous, a multilevel crossclassified cumulative ordered logit model is a more appropriate model for the response variables considered in this paper.

3.3.2 Model Specification

Let $y_{ij(kl)}$ denotes the ordinal outcome variable of interest for individual i from household j, interviewed by interviewer k, and sampled in PSU l three years ago. Parenthesis around k and l is used to indicate the cross-classification of interviewers and areas. The outcome variable is a four-point-scale index, which takes four-response categories C = 1, 2, 3, 4, where a larger value indicates the individuals are more environmentally friendly behaved. In an ordinal multilevel cross-classified model, a set of C - 1 or C = 1, 2, 3 equations are estimated,

assuming the effects of covariates to be constant irrespective of the category, c, being considered. Therefore, the general form of the multilevel cross-classified cumulative ordered logit model is represented as:

$$\log \left[\frac{\Pr(y_{ij(kl)} \leq c)}{\Pr(y_{ij(kl)} > c)} \right] = \operatorname{logit}(\gamma_{cij(kl)}) = \alpha_{c} - (\boldsymbol{\beta}^{T} \mathbf{X}_{ij(kl)} + u_{j} + v_{k} + w_{l}), \qquad c = 1, 2, 3$$

where $\mathbf{X}_{ij(kl)}$ is a vector of individual- , household-, interviewer-, and PSU-level covariates and interactions; $\boldsymbol{\beta}$ is a vector of coefficients for the explanatory variables $\mathbf{X}_{ij(kl)}$ and α_c is the threshold parameter, representing the intercepts in the linear relationship between the logodds of a response of $c \leq 3$ and the predicted variables specified in the model (for example, α_2 is the log-odds of being in either category 1 or 2 (rather than 3 or above) for an individual with the explanatory variables equal zero). Since the logits of the cumulative response probability are modelled, the intercepts are ordered with $\alpha_1 < \alpha_2 < \alpha_3$.

The parameters u_j , v_k and w_l are the random effect terms for household, interviewer and area respectively. These random terms are assumed to be mutually independent and identical distributed, in which they follow a normal distribution with mean equals to zero and the corresponding variances, i.e., $u_j \sim N(0, \sigma_u^2)$, $v_k \sim N(0, \sigma_v^2)$ and $w_l \sim N(0, \sigma_w^2)$ where σ_u^2 , σ_u^2 and σ_u^2 are the household-level, interviewer-level and area-level variances respectively.

In this model, the effect of the vector of the explanatory variables $\mathbf{X}_{ij(kl)}$ on the outcome variable is assumed to be constant, and this is known as the proportional odds assumption. Furthermore, we also assume all random effects to be independent of the categories.

The multilevel classified cumulative ordered logit model can also be written as a linear model in terms of a latent continuous variable $y_{ij(kl)}^*$ which underlies the observed ordinal variable $y_{ij(kl)}$ (Snijders and Bosker, 2012). The relationship between the observed and the unobserved outcome variable is as follows:

$$y_{ij(kl)} = \begin{cases} 1, & \text{if } y_{ij(kl)}^* \le \alpha_1 \\ 2, & \text{if } \alpha_1 < y_{ij(kl)}^* \le \alpha_2 \\ 3, & \text{if } \alpha_2 < y_{ij(kl)}^* \le \alpha_3 \\ 4, & \text{if } \alpha_3 < y_{ij(kl)}^* \end{cases}$$

where $\alpha_1 < \alpha_2 < \alpha_3$ are the thresholds to be estimated.

Therefore, a linear regression model for the latent variable $y_{ij(kl)}^*$ can be defined as:

$$y_{ii(kl)}^* = \mathbf{\beta}^{T} \mathbf{X}_{ii(kl)} + u_i + v_k + w_l + e_{ii(kl)}^*$$

where $e_{ij(kl)}^*$ is the unobserved individual-level error term in the linear regression model and u_j , v_k and w_l are the random effect terms for household, interviewer and area respectively. Here, $e_{ij(kl)}^*$ are assumed to follow a standard logistic distribution with mean equal to zero and variance, $\sigma_e^{*2} = \pi^2/3 \approx 3.29$. Since $y_{ij(kl)}^*$ is an unobserved variable, the scale of the error term is a fixed constant (Hedeker, 2008).

Unlike the straight forward calculation of the Variance Partitioning Coefficient (VPC) in a multilevel model for continuous outcomes, there are multiple ways in calculating the VPC for multilevel cumulative ordered logit model, such as model linearization, simulation, binary linear model and latent variable approaches (Goldstein, 2011). Among these methods, the most commonly used is the latent variable approach.

In the latent representation of the multilevel classified cumulative ordered logit model, the total variation is the sum of the level one variance and the three random effect terms.

Therefore, the total variance can be expressed as:

Total Variation =
$$\sigma_e^{*2} + \sigma_u^2 + \sigma_v^2 + \sigma_w^2 = 3.29 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2$$
.

Hence, the VPCs for household, interviewer, and area levels can be written as:

$$\begin{aligned} \text{VPC}_{household} &= \frac{\text{between household variation}}{\text{total variation}} = \frac{\sigma_u^2}{3.29 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2} \\ \text{VPC}_{interviewer} &= \frac{\text{between interviewer variation}}{\text{total variation}} = \frac{\sigma_v^2}{3.29 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2} \\ \text{VPC}_{area} &= \frac{\text{between area variation}}{\text{total variation}} = \frac{\sigma_w^2}{3.29 + \sigma_u^2 + \sigma_v^2 + \sigma_w^2} \end{aligned}$$

where σ_u^2 , σ_v^2 and σ_w^2 are the household-level, interviewer-level and area-level variances respectively (Hedeker, 2008; Goldstein, 2011). These VPCs are the proportion of explained variance at the corresponding levels. They can be interpreted as the proportion of the total variation in the propensity to have a higher value of $y_{ij(kl)}$ that is due to the corresponding levels.

3.3.3 Predicted Response Probability

As the interpretation of the estimates and the odds-ratios in multilevel cumulative ordered logit model is not straight-forward, the predicted cumulative response probability and the response probability are considered in this paper. The predicted cumulative response probability for individual i from household j, interviewed by interviewer k, and living in PSU l can be calculated as:

$$\widehat{\gamma}_{cij(lk)} = \widehat{\Pr}(y_{ij(kl)} \le c) = \frac{\exp[\widehat{\alpha}_{c} - (\widehat{\boldsymbol{\beta}}^{T} \mathbf{X}_{ij(kl)} + \widehat{u}_{j} + \widehat{v}_{k} + \widehat{w}_{l})]}{1 + \exp[\widehat{\alpha}_{c} - (\widehat{\boldsymbol{\beta}}^{T} \mathbf{X}_{ij(kl)} + \widehat{u}_{i} + \widehat{v}_{k} + \widehat{w}_{l})]}, \quad c = 1, 2, 3$$

where $\hat{\alpha}_c$, $\hat{\beta}$, \hat{u}_j , \hat{v}_k and \hat{w}_l are the sample estimates of α_c , β , u_j , v_k and w_l .

The predicted response probability can be further calculated as:

$$\widehat{\pi}_c = \widehat{Pr}(y_{ij(kl)} = c) = \widehat{Pr}(y_{ij(kl)} \le c) - \widehat{Pr}(y_{ij(kl)} \le c - 1) = \widehat{\gamma}_{cij(lk)} - \widehat{\gamma}_{c-1ij(lk)}.$$

In order to calculate the predicted probability, we need to specify a set of arbitrary values for the estimates of the fixed and random effects. In particular, the random effects for the household-level, interviewer-level and area-level can be handled in three different ways. As a result, three different types of predicted response probability can be calculated: *conditioned probability*, *population-averaged probability* and *cluster-averaged probability* (Skrondal and Rabe-Hesketh, 2009). A very comprehensive guideline on how these probabilities are computed and a detailed example are discussed by Skrondal and Rabe-Hesketh (2009). In addition, Grilli and Rampichini (2012) also provide an example on how these predicted response probabilities can be applied on actual data.

The conditional probability is the prediction for a unit in a hypothetical cluster by fixing the random effects to an arbitrary value (Skrondal and Rabe-Hesketh, 2009). In many cases, we hold the random effect terms $(u_j, v_k \text{ and } w_l)$ at their means of zero. However, as the response probabilities (or the cumulative probabilities) are non-linearly related to the higher-level random terms, the conditional probabilities when the random effect terms are set to zero are not equivalent to the mean probabilities but the median probabilities (Steele, 2009;2011). In this specific case where the random effect terms are fixed at zero, the conditional probability is also known as the cluster-specific probability.

The population-averaged probability is the prediction for a unit in a new cluster while the cluster-averaged probability is the prediction for a new unit in a specific sample cluster (Skrondal and Rabe-Hesketh, 2009). The random effect terms $(u_j, v_k \text{ and } w_l)$ of the population-averaged probability are the averages across their corresponding distributions while the estimated distributions for the j^{th} household, k^{th} interviewer and l^{th} area are used

for the cluster-averaged probability (Skrondal and Rabe-Hesketh, 2009; Grilli and Rampichini, 2012). Since the random effects for the three clusters are unknown, the average over the corresponding posterior distributions are used (Skrondal and Rabe-Hesketh, 2009).

3.3.4 Model Estimation and Modelling Strategy

The models are estimated by Markov Chain Monte Carlo (MCMC) methods in the MLwiN software using starting values from the estimates obtained by first order penalised (or predictive) quasi likelihood (PQL) (Goldstein, 2011; Browne, 2015). A burn-in length of 5,000 and 2,500,000 iterations are used. All the estimations are performed in MLwiN version 2.25 through R (R Core Team, 2016) using the package R2MLwiN (Zhang *et al.*, 2016). In order to speed up the estimation process, five models (burn-in length of 5,000 and iteration of 500,000) with the same model specification but different starting values are generated. Afterwards, theses five models are manually combined by joining the MCMC chains using the package coda (Plummer *et al.*, 2006) in R.

Model building starts with only one random term at the individual level. Higher level random effects are then included in the model and significance for each term is tested simultaneously using a Wald test. Since variance cannot be negative, a one-sided *p*-value is used for significant testing (Snijders and Bosker, 2012). Normally, sample weights should be applied when analysing survey data. However, MCMC estimation in the MLwiN software does not allow the inclusion of weight. The sensitivity analysis from the Section 2.6 in the previous chapter also shows that results are not sensitive to weights. As recommended by Snijders and Bosker (2012), design variables are included in the model. Therefore, variables that are related to the sample composition (i.e., General Population Sample, Ethnic Minority Boost Sample and the former British Household Panel Survey) and are used in the models to derive sample weights (government office region, residential area and ethnicity) are included in the analysis. Since variables which are used to derive sample weights are able to account for some key elements of the variation in the section probabilities, they are all included in the final model even if not significant. However, it should be noted that these variables do not account for all variations that are contributed by the selection probabilities.

The random structure is first identified before including blocks of explanatory variables as fixed effects. A forward selection strategy is then adopted for the selection of explanatory variables. Information about sample composition, government office region and residential area is added to the null model before the inclusion of other explanatory variables. Blocks of explanatory variables at the individual-level (in the following order: individual sociodemographics, personal values and environmental concerns and attitudes) are considered before the household level variables (in the following order: household

sociodemographics, household structure, accommodation characteristics and neighbourhood characteristics). As already mentioned, sample composition, government office region, residential area and ethnicity are related to the sample weights. These variables, together with the dummy variables which indicate the presence of pensioners, children, younger than two years old, children aged between three and four, five and eleven, and twelve and fifteen in the household, as well as the categorical variable for household structure are always included in the model as control variables regardless of their significances. The presence of pensioner and children from different age-groups are important information about the household characteristics and we want to examine how the age of children affects adult household members' behaviours. Therefore, these variables are also included in the model. Moreover, one of the main interests of this paper is to investigate the role of households in individuals' behaviours so it is important to include the categorical variable for household structure into the model.

For model comparison, the deviance information criterion (DIC) is used (Snijders and Bosker, 2012). The model with a smaller DIC is a more preferable model. The Wald test is used to test the significance of each categorical variables in the fixed effects as it allows multiple parameters for a categorical variable to be tested simultaneously (Snijders and Bosker, 2012). The least significant variable with *p*-value larger than 0.05 is removed from the model. Models are re-fitted until all variables in the same block are statistically significant at the 5% significance level. In the cases where the individual-level variable becomes insignificant when household-level variables are added, the insignificant individual variable is removed.

3.3.5 Model Validations and Diagnostics

Relevant model diagnostic tests are conducted to check the validation and assumptions of the final models. In order to test the assumptions of normality, normal residual plots are used. Meanwhile, the standardised residuals are plots against the predicted values to test the assumption homogeneity of variance. As shown in the normal plots in Figures B.6.1, B.7.1 and B.8.1 in Appendix B, we can confirm the assumption of normality is valid for all models. Based on the residual plots in Figures B.6.2, B.7.2 and B.8.2, the homoscedasticity of variance of residual errors assumption is also valid.

We compare the final multilevel cumulative ordered logit models with a similar model that has the assumption partially relaxed. The DIC statistics for the relaxed models are 61,775.0, (transport-related environmental behaviour), 79.854.8 (home-related environmental behaviour) and 77,363.2 (purchasing-related environmental behaviour) respectively. Compared to the corresponding DIC statistics from the final models in Table 3-8, Table 3-9 and Table 3-10, the differences in DIC statistics between the relaxed and the corresponding

final models are negligible. Therefore, the assumptions of the proportional odds assumption for multilevel cumulative ordered logit model are valid.

Finally, trace plots and kernel density plots for the posterior distributions for the three models are presented in Figures B.6.3, B.7.3 and B.8.3. These plots provide evidence that the MCMC chains for the three models reach convergence. The effective sample size and Raftery-Lewis diagnostic statistics are also computed for each of the models (see Table B.6.4, B.7.4 and B.8.4). These statistics further confirm convergences are obtained for the three ordinal outcomes.

3.4 Results and Discussion

3.4.1 Exploration of Random Effects Specifications

First, the random structures of the empty multilevel models are explored. The household random effect is examined, followed by the interviewer and area random effects and finally the cross-classified structure between the interviewer and area random effects. Table 3-7 presents the estimated variances, the corresponding standard errors, VPCs and DIC statistics for the multilevel models on three different outcome variables. For the transport-related outcome (Outcome 1), the inclusion of the household random effect (Model 1.1) reduces the DIC statistics of the empty model (Model 1.0), indicating that the two-level hierarchical model (Model 1.1) has a better fit than Model 1.0. Then, the Interviewer and PSU random effects are included one at a time into the two-level model with the household random effect. The DIC statistics of both three-level hierarchical models (Model 1.2 and Model 1.3) have substantially decreased compared to Model 1.1, demonstrating that the inclusion of either of these two random effects can explain a larger proportion of the total variation of the model. Since interviewers and PSUs are cross-classified, an additional model incorporating the crossclassified structure (Model 1.4) is also explored to take both interviewer and area effects into consideration simultaneously. In comparison with Model 1.1, the household random effect variance of Model 1.4 has decreased by around 45%. The substantial reduction of the household random effect variance is due to the partitioning of the household variance into the interviewer and PSU variances. All three random terms are statistically significant at the 1% level, suggesting that behaviours of the individuals from the same household are more alike than individuals from other households. Similarly, there are more homogeneities in the responses between individuals interviewed by the same interviewer than those interviewed by different interviewers. In particular, the VPCs for the household, interviewer and area random effects for Model 1.4 are 0.213, 0.138 and 0.038 respectively, suggesting that around 21% of the variation in individuals' transport-related environmental behaviours is due to the

household effect while 14% can be explained by interviewer effect. Meanwhile, the area effect also accounts for around 4% of the individuals' variation.

The random effects specifications of the home-related outcome (Outcome 2) and purchasingrelated outcome (Outcome 3) are similar to that of the transport-related outcome. Both twolevel hierarchical level models (Model 2.1 and Model 3.1) have smaller DIC statistics than their corresponding one-level models (Model 2.0 and Model 3.0). The inclusion of interviewer and PSU random effects also further reduce the DIC statistics (comparing Models 2.2 and 2.3 with Model 2.1; Models 3.2 and 3.3 with Model 3.1). These results demonstrate that household, interviewer and PSU explain a large part of the total variation of the responses. Finally, the cross-classified structure between the interviewers and PSUs are taken into account (Model 2.4 and Model 3.4). Compare to the two-level hierarchical level model (Model 2.1), the household random effect variance for the home-related outcome is reduced by approximately 15%. Meanwhile, the household random effects variance becomes threequarters of its original value (Model 3.1 compared with Model 3.4) for the purchasing-related outcome. In addition, all random effects are significant for both Outcome 2 and Outcome 3, implying that for these two outcomes, the cross-classified model is also the most preferred model. Similar to the Outcome 1, the largest proportion of the individuals' variation for Outcome 2 and Outcome 3 can be explained by the household random effect (37% and 31% respectively), followed by the interviewer random effect (4% and 8% respectively) and the area random effects (2% and 2% respectively).

3.4.2 Discussion of the Final Models - Random Effects

One of the focuses of this paper is to investigate how households influence individuals' environmental behaviours and how interviewers affect individuals' responses to proenvironmental behaviour questions. Therefore, this section aims to explore the changes in all random effects after controlling for individual-level and household-level variables. All results are in comparison to Models 4 (i.e., Models 1.4, 2.4 and 3.4) from the previous section (now in this section, they are referred to as the respective null models). The estimates of the household, interviewer and area effects as blocks of explanatory variables are added to the null models are shown in Tables 3-8, 3-9 and 3-10 respectively. In these three models, as block of explanatory variables are included in the null models, the DIC statistics decrease substantially.

For transport-related outcome (Outcome 1), the household variance accounts for 21.3% of the total variation in explaining individuals' behaviours, while the interviewer variance accounts for 13.8% and the area variance accounts for 3.8% in the null model (see Table 3-8). As individual sociodemographic variables are added into the model, the total variance

explained by the household random effect increases to 24.7%. About a quarter of the variation is explained by the variation in individual sociodemographic variables across the households. Adjusting the individual personal values and attitudes towards the environment reduces the total variation by approximately 6%, though the VPC is still higher than the null model. As expected, household variance reduces substantially by around 25% when household level variables are included in the model, that is, one-fourth of the individuals' variation within households can be explained by the household-level variables. The total variation explained by the household also reduces by 23.3% to 18.6%. Meanwhile, the inclusion of individual-level variables reduces the total variation explained by the interviewer random effect. However, further inclusion of household level variables increases the VPC from 6.8% to 7.3%. As interviewers are allocated to households based on geographical proximity, it is not surprising to note that there is a substantial decrease in the interviewer variance when information on government office region is introduced to the model. On the other hand, when both individual- and household-level variables are taken into consideration, the area effect diminishes but remains significant.

Table 3-7 Variances and DICs for Empty Multilevel Models on Three Outcome Variables: Transport-, Home-, and Purchasing-related Pro-Environmental Behaviours

Model	Random Term	Term	Οι	itcome 1 - '	Transp	ort		Outcome 2 - Home				Outcome 3 - Purchasing			
	in the Model		(Model 1)			(Model 2)					(Mode	13)			
			Variance	(S.E.)	VPC	DIC	Variance	(S.E.)	VPC	DIC	Variance	(S.E.)	VPC	DIC	
0	Empty					72661.2				89917.9				86714.2	
1	Household	Household	2.096	(0.088)***	0.389	68646.9	2.472	(0.084)***	0.429	83402.9	2.387	(0.095)***	0.420	81706.4	
2	Household and	Household	1.418	(0.076)***	0.263	68016.8	2.203	(0.081)***	0.382	83236.0	1.930	(0.090)***	0.340	81452.1	
	PSU	PSU	0.676	(0.043)***	0.126		0.270	(0.027)***	0.047		0.454	(0.038)***	0.080		
3	Household and	Household	1.418	(0.076)***	0.259	66938.5	2.151	(0.080)***	0.374	83236.8	1.791	(0.087)***	0.315	81350.5	
	Interviewer	Interviewer	0.763	(0.058)***	0.140		0.317	(0.030)***	0.055		0.607	(0.044)***	0.107		
4	Household, PSU	Household	1.141	(0.069)***	0.212	66809.3	2.147	(0.079)***	0.373	82996.9	1.756	(0.078)***	0.313	80402.8	
	and Interviewer	Interviewer	0.745	(0.057)***	0.139		0.217	(0.023)***	0.038		0.471	(0.039)***	0.084		
	cross-classified	PSU	0.203	(0.025)***	0.038		0.107	(0.023)***	0.019		0.093	(0.023)***	0.017		

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Household, interviewer and area random effects account for 37.3%, 3.8% and 1.9% of the total variation in explaining individuals' home-related pro-environmental behaviours for the null model (Outcome 2, see Table 3-9). Once the individual- and household-level variables are added into the model, the household VPC decreases to 36.0%. The inclusion of individuallevel variables manages to reduce a larger proportion of the household random effect than the inclusion of variables at the household level. This may be explained by the homogeneity nature of the household, that is, household members share many similar sociodemographic characteristics and attitudes, and therefore, household effect can be viewed as aggregated individual effect. Furthermore, as home-related behaviours include turning down the heat and switching off the light, it is reasonable to find that individuals living in the same household behave similarly in their daily life. Although the interviewer and area variances are relatively smaller than the household variance in the final model (1.7% and 1.1%) compare to 36.0%), both of them remain significant in explaining variation among individuals. As presented in Table 3-9, the VPCs of interviewer and area decrease as variables at individual and household levels are included in the model. Similar to the transport-related behaviours, there is a substantial reduction in interviewer variance when information about the government office region is added to the model for home-related behaviours. Again, this can be explained by the allocation mechanism of cases among interviewers.

The estimates of the household, interviewer and area random effects and the corresponding VPCs for individuals' purchasing-related environmental behaviours are presented in Table 3-10. In the null model, 31.3%, 8.4% and 1.7% of the individuals' variation can be explained by household, interviewer and area effects respectively. As the individual-level variables are included in the model, the household VPC decreases substantially from 31.6% to 28.3%. However, the inclusion of household-level variables does not have any effect on the household random effect variance. This further provides evidence to support our early hypothesis in Chapter 2 that households consist of individuals who share similar or common sociodemographics, personal values and attitudes so that household effects can be treated as aggregated individual effects. Meanwhile, once the individual- and household-level variables are added into the model, there is also a considerable reduction in the area random effect (VPC drops by approximately 50% from the null model (1.7%) to the final model (0.9%)). However, the interviewer random effect does not change much even when all significant individual- and household-level variables are included in the final model (VPC=8.3%). Nevertheless, both interviewer and area random effects remain significant despite their magnitudes being relatively small.

Table 3-8 Estimates of the Household, Interviewer and PSU Random Effect Variances as Blocks of Explanatory Variables are added to the Cross-classified Multilevel Model: Outcome 1 – Transport-related Pro-Environmental Behaviours

Fixed Effects Parameters (no. of parameters)	Estimates of the Household Random Effect Variance		Estimates of the Interviewer Random Effect Variance			Estimates of the PSU Random Effect Variance			DIC	
	Variance	(S.E.)	VPC	Variance	(S.E.)	VPC	Variance	(S.E.)	VPC	_
None	1.141	(0.069)***	0.212	0.745	(0.057)***	0.139	0.203	(0.025)***	0.038	66,809.3
Added sampling design (14)	1.120	(0.066)***	0.228	0.332	(0.031)***	0.068	0.179	(0.024)***	0.037	66,608.1
Added individual sociodemographics (27)	1.244	(0.074)***	0.246	0.346	(0.032)***	0.068	0.176	(0.026)***	0.036	64,232.1
Added individual personal value (23)	1.186	(0.073)***	0.238	0.336	(0.031)***	0.067	0.168	(0.024)***	0.034	63,871.9
Added individual environmental value (3)	1.152	(0.070)***	0.233	0.334	(0.031)***	0.068	0.157	(0.025)***	0.032	63,624.1
Added household sociodemographics (2)	0.855	(0.060)***	0.186	0.333	(0.030)***	0.072	0.120	(0.021)***	0.026	61,880.6
Added household structure (8)	0.862	(0.062)***	0.187	0.334	(0.030)***	0.073	0.120	(0.021)***	0.026	61,838.3
Added accommodation characteristics (10)	0.850	(0.061)***	0.185	0.335	(0.030)***	0.073	0.116	(0.021)***	0.026	61,779.1
Added neighbourhood characteristics (2)	0.853	(0.061)***	0.186	0.335	(0.030)***	0.073	0.115	(0.021)***	0.025	61,776.5

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 3-9 Estimates of the Household, Interviewer and PSU Random Effect Variances as Blocks of Explanatory Variables are added to the Cross-classified Multilevel Model: Outcome 2 – Home-related Pro-Environmental Behaviours

Fixed Effects Parameters (no. of parameters)		Estimates of the Household Random Effect Variance		Estimates of the Interviewer Random Effect Variance			Estimates of the PSU Random Effect Variance			DIC
	Variance	(S.E.)	VPC	Variance	(S.E.)	VPC	Variance	(S.E.)	VPC	_
None	2.147	(0.079)***	0.373	0.217	(0.023)***	0.038	0.107	(0.023)***	0.019	82,996.9
Added sampling design (14)	2.157	(0.079)***	0.382	0.112	(0.016)***	0.020	0.095	(0.023)***	0.017	82,926.8
Added individual sociodemographics (28)	2.044	(0.078)***	0.371	0.101	(0.015)***	0.018	0.074	(0.021)***	0.014	80,945.2
Added individual personal value (21)	2.009	(0.078)***	0.368	0.096	(0.014)***	0.018	0.067	(0.021)***	0.012	80,641.0
Added individual environmental value (7)	1.938	(0.076)***	0.360	0.093	(0.014)***	0.017	0.062	(0.021)***	0.012	79,985.1
Added household sociodemographics (2)	1.934	(0.076)***	0.360	0.093	(0.014)***	0.017	0.062	(0.020)***	0.012	79,972.8
Added household structure (8)	1.943	(0.076)***	0.361	0.093	(0.014)***	0.017	0.056	(0.021)**	0.010	79,889.3
Added accommodation characteristics (5)	1.934	(0.076)***	0.360	0.093	(0.014)***	0.017	0.059	(0.021)**	0.011	79,855.5
Added neighbourhood characteristics (2)	1.934	(0.076)***	0.360	0.093	(0.014)***	0.017	0.058	(0.022)**	0.011	79,852.0

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 3-10 Estimates of the Household, Interviewer and PSU Random Effect Variances as Blocks of Explanatory Variables are added to the Cross-classified Multilevel Model: Outcome 3 – Purchasing-related Pro-Environmental Behaviours

Fixed Effects Parameters (no. of parameters)	Estimates of the Household Random Effect Variance		Estimates of the Interviewer Random Effect Variance			Estimates of the PSU Random Effect Variance			DIC	
(0. p)	Variance	(S.E.)	VPC	Variance	(S.E.)	VPC	Variance	(S.E.)	VPC	_
None	1.756	(0.078)***	0.313	0.471	(0.039)***	0.084	0.093	(0.023)***	0.017	80,402.8
Added sampling design (14)	1.763	(0.079)***	0.316	0.442	(0.037)***	0.079	0.090	(0.024)***	0.016	80,388.2
Added individual sociodemographics (24)	1.758	(0.080)***	0.315	0.456	(0.038)***	0.082	0.074	(0.021)***	0.013	78,755.3
Added individual personal value (22)	1.634	(0.076)***	0.301	0.448	(0.037)***	0.083	0.049	(0.024)**	0.009	78,211.5
Added individual environmental value (6)	1.490	(0.074)***	0.283	0.439	(0.036)***	0.083	0.046	(0.021)**	0.009	77,417.7
Added household sociodemographics (2)	1.477	(0.074)***	0.281	0.437	(0.036)***	0.083	0.048	(0.021)**	0.009	77,398.9
Added household structure (8)	1.487	(0.073)***	0.283	0.438	(0.036)***	0.083	0.045	(0.021)*	0.008	77,393.8
Added accommodation characteristics (10)	1.489	(0.074)***	0.283	0.438	(0.036)***	0.083	0.043	(0.021)*	0.008	77,365.8

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

3.4.3 Discussion of the Final Models - Fixed Effects

After examining the random effects of the three final models, the following section discusses the fixed effects. As discussed previously, the inclusions of both individual- and household-level variables reduce the total variation explained by household, interviewer and area random effects. This section focuses on these explanatory variables which are important in explaining the individuals' variation in three types of behaviours. The estimated odds ratios for the three final models are presented and the corresponding significant variables are then discussed. For some selected variables, their predicted probabilities will also be presented and discussed. The interpretation of these fixed effect covariates is conditional on the presence of all other fixed effects in the corresponding models.

3.4.3.1 OUTCOME 1 - Transport-related Pro-Environmental Behaviours

The estimated odds ratios for the final cross-classified multilevel model on the transport-related pro-environmental behaviours are presented in Table 3-11. The significant variables at individual and household levels in the final model will be discussed.

Table 3-11 Estimated Coefficients for the Final Cross-Classified Multilevel Model: Outcome 1
- Transport-related Environmental Behaviour

Variable	Category	OR	(S.E.)
(Reference Category)			
Intercept 1		0.979	(0.251)
Intercept 2		0.065	(3.760)***
Intercept 3		0.004	(60.14)**
Individual So	ociodemographic Variables		
Age (16-30)	31-45	0.591	(0.079)***
	46-60	0.496	(0.101)***
	61-75	0.610	(0.134)***
	76 or above	0.389	(0.274)***
Marital Status (Currently married/	Currently not married	1.352	(0.033)***
cohabitation)	Missing	0.797	(0.332)
Employment Status (Employed)	Self-employed	0.744	(0.069)***
	Unemployed	1.226	(0.056)**
	Retired	1.068	(0.059)
	Full-time Student	1.997	(0.036)***
	Other Employment Status	0.774	(0.068)***
	Missing	1.007	(2.202)

Variable	Category	OR	(S.E.)
(Reference Category)			
Highest education level (Degree)	Other Higher Degree	0.844	(0.055)***
	A-level or Equivalent	0.826	(0.049)***
	GCSE or Equivalent	0.837	(0.051)***
	Other Qualification	0.730	(0.077)***
	No Qualification	0.731	(0.079)***
	Missing	0.873	(0.171)
Ethnicity (White)	Mixed	0.938	(0.118)
	Asian	0.897	(0.086)
	Black	0.976	(0.097)
	Other Ethnic Group	1.029	(0.170)
	Missing	1.105	(0.153)
Born in the UK (Yes)	No	1.238	(0.041)***
	Missing	1.152	(0.091)
Individual monthly income	Log transformed income	1.122	(0.023)***
	Quadratic term of log transformed income	0.980	(0.003)***
<u>Individual F</u>	Personal Value Variables		
Belong to a religion (Yes)	No	1.092	(0.027)**
	Missing	0.100	(15.675)
Level of interest in politics (Very	Fairly	0.922	(0.050)
interest)	Not very	0.809	(0.060)***
	Not at all interested	0.750	(0.070)***
	Missing	0.524	(1.306)
Supported party (Conservative)	Labour	1.090	(0.037)*
	Liberal Democrat	1.230	(0.048)***
	Scottish National Party	1.064	(0.098)
	Plaid Cymru	0.862	(0.210)
	Green Party	2.008	(0.039)***
	Ulster Unionist	1.100	(0.158)
	SDLP	0.653	(0.300)*
	Alliance Party	1.608	(0.130)*
	Democratic Unionist	0.955	(0.187)
	Sinn Fein	1.102	(0.181)
	Other party	0.965	(0.048)
	Cannot vote	1.662	(0.058)***
	None	1.120	(0.070)
	Missing	1.067	(0.053)
Voluntary work in the last 12 months	No	0.690	(0.048)***
(Yes)	Missing	-	-
Donation to charity in the last 12	No	0.835	(0.037)***
months (Yes)	Missing	1.364	(0.441)
	Missing	1.504	(0.771)

Variable	Category	OR	(S.E.)
(Reference Category)			
<u>Individual Envi</u>	ronmental Value Variables		
Environmental concern	Environmental Concern Score	1.044	(0.003)***
Believe green is an alternative living	Disagree	1.185	(0.024)***
style (Agree)	Missing	1.015	(0.153)
<u>Household Soc</u>	riodemographic Variables		
Ownership of car(s) (Yes)	No	8.652	(0.006)***
	Missing	1.025	(0.394)
Household	d Structure Variables		
Pensioner(s) in household (Yes)	No	1.108	(0.051)
Children aged 0-2 in household (Yes)	No	1.094	(0.053)
Children aged 3-4 in household (Yes)	No	1.058	(0.057)
Children aged 5-11 in household (Yes)	No	0.903	(0.052)*
Children aged 12-15 in household (Yes)	No	0.955	(0.053)
Household structure (Single household without children)	Single household with children	0.815	(0.106)*
	Non-single household without children	1.304	(0.044)***
	Non-single household with children	1.318	(0.055)***
Household Accommo	dation Characteristics Variable	<u>es</u>	
Tenure type (Home owned outright)	Home owned with mortgage	0.867	(0.047)***
	Home social rent	0.772	(0.071)***
	Home private/ employer rented	0.992	(0.056)
	Other	0.767	(0.470)
	Missing	0.894	(0.168)
Dwelling type (Detached house)	Semi-detached house/ bungalow	1.205	(0.032)***
	End terraced/ terraced house/ bungalow	1.423	(0.030)***
	Flat/ maisonette	1.386	(0.043)***
	Others	1.039	(0.154)
	Missing	0.891	(0.355)
<u>Neighbourhoo</u>	d Characteristic Variables		
Trash, junk and rubbish on the street in	No	1.067	(0.087)
the neighbourhood (Yes)	Missing	1.521	(0.210)

Variable	Category	OR	(S.E.)
(Reference Category)			
Samplin	ng Design Variables		
Sample composition (GPS)	Former BHPS	0.987	(0.043)
	EMBS	0.994	(0.074)
Government office region (North East)	North West	1.001	(0.165)
	Yorkshire and the Humber	1.429	(0.120)*
	East Midlands	1.110	(0.155)
	West Midlands	0.853	(0.206)
	East of England	1.499	(0.111)*
	London	2.780	(0.059)***
	South East	1.241	(0.131)
	South West	1.062	(0.168)
	Wales	0.851	(0.210)
	Scotland	1.395	(0.128)
	Northern Ireland	0.488	(0.394)***
Residential Area (Urban)	Rural	0.740	(0.053)***

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Significant Individual-level Variables

Individual sociodemographic, personal value and environmental attitude variables are found to be significant in explaining the individuals' transport-related behaviour. Significant individual sociodemographic variables include age, marital status, employment status, individual monthly income, education level and a dummy variable to indicate whether or not the respondent is born in the UK; significant personal value variables include a dummy variable to indicate whether or not the respondent belongs to a religion, level of interest in politics, party affiliation, involvement in voluntary work and charity donation; and significant environmental concern and attitude variables include the environmental concern score and a dummy variable that indicate whether or not the respondent agrees green is an alternative living style.

All odds ratios of the four age dummies variables are less than one, indicating that individuals in these age groups engage in less transport-related environmental behaviours (or travel green) than the reference group (16-25 years old). People who are not currently married nor in a cohabitation relationship are more environmentally friendly than those who are living with their partners in their daily transport choices. In terms of employment status, unemployed individuals and students behave more environmentally responsibly than the employed when they are travelling. However, those who are self-employed are less likely to engage in environmentally friendly transport-behaviours. On the other hand, individuals earning a higher income are more likely to prefer a greener transport. Furthermore, all six

coefficients of the education dummies are less than one, implying that less educated people tend to engage in less pro-environmental transport-related behaviours. Ethnicity is not significant in explaining the individuals' transport choices.

Surprisingly, people without religion are more environmentally friendly in their travelling habits than those who belong to a religion. This contradicts with recent studies which have demonstrated a positive relationship between religiousness and environmentally friendly behaviours (Pepper, Jackson and Uzzell, 2011; Hope and Jones, 2014). As expected, those who are less interested in politics use less green transportation than those who are interested in politics. Labour, Liberal Democrat, Green Party and Alliance Party supporters, meanwhile, are more likely to engage in greener transport-related behaviours than the Conservative supporters. Not surprisingly, people who are involved in pro-social activities (such as volunteering work and donation to charity) also tend to behave environmentally responsible in transport choices, which is also considered as a pro-social activity.

People who are more concerned about environmental issues tend to behave greener when they decide how to travel. This result is not surprising as many previous literatures have shown a positive relationship between environmental attitudes and behaviours. Furthermore, those who disagree with the statement 'green is an alternative living style' also behave more environmentally friendly in the transport-related behaviours. As discussed in the previous working paper, those who are used to a green living style would not think green is an alternative. Only those who are not would consider it as an alternative living style.

Significant Household-level Variables

A wide range of household-level variables are found to be significant in explaining individuals' transport-related behaviours. These variables include ownership of car, presence of children aged between five and eleven in the household, household structure, tenure type, dwelling type and residential area.

Individuals from households without a car are more environmentally friendly in their choice of transport. It is possible that they do not own a car and hence they are forced to use other means of transport, such as using public transport, cycling or walking. However, it should be noted that the reverse causation is also possible, that is, some people prefer greener ways to travel so they decide not to own a car.

One of the main interests in this paper is to investigate the role of household in individuals' transport-related environmental behaviours. Paper 1 shows that household structure has a significant role in explaining general environmental behaviours. Similar to the previous working paper, people's transport-related behaviours are also greatly influenced by the

household structure. Single householders with children are found to be less environmentally friendly than the single householders without children in the transport-related domain. However, regardless of the presence of children in the household, non-single householders travel greener than the single householders without children. Meanwhile, individuals living with children between five to eleven years old tend to be less environmentally friendly. However, unlike the general environmental behaviours, the presence of children below two years old does not have any significant effect on transport-related behaviours. To further investigate the effect of household structure on the individuals' transport-related behaviours, the population-average predicted probabilities are calculated for all household structures. Figure 3-2 shows the predicted probabilities for the transport-related pro-environmental behaviours. As shown in the graph, the predicted probability for an individual from a single household with children to have very low engagement in the transport-related environmental behaviours is the highest among all household types.

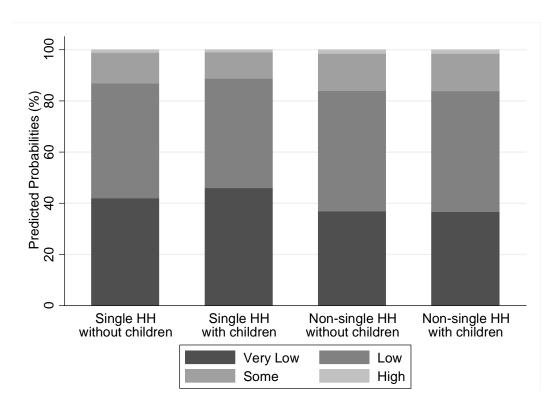


Figure 3-2 Population-Average Predicted Probabilities for Transport-related Pro-Environmental Behaviour

Household accommodation characteristics are found to be significant in explaining energy use indirectly in the literature (Utley and Shorrock, 2006). These variables are also included in the final model. Both tenure and dwelling types are significant in explaining transport-related behaviours. In particular, those who are living in homes owned with mortgage and social rent homes are less likely to use greener travelling methods than those living in homes outright. Furthermore, semi-detached house, end terraced house and flat residents tend to be greener than those residing in detached house.

Unlike the general pro-environmental behaviours, no North-South difference is observed for transport-related behaviours. Comparing to those living in the North East, people from Yorkshire and the Humber, London and East of England use greener transports. On the other hand, Northern Irelanders are less environmentally friendly. For London, it is not surprising to observe such a result. London's traffic is always very busy and given the implementation of congestion charge in the capital, it is reasonable for the Londoners decide to use public transports, especially the tube system, rather than driving. Finally, compare to the urban residents, rural residents also use less green transportations.

3.4.3.2 OUTCOME 2 - Home-related Pro-Environmental Behaviours

The estimated odds ratios for the final cross-classified multilevel model on the transport-related pro-environmental behaviours are presented in Table 3-12. The significant variables at individual- and household-level in the final model will be discussed.

Table 3-12 Estimated Coefficients for the Final Multilevel Cross-Classified Model: Outcome 2

- Home-related Environmental Behaviours

Variable	Category	OR	(S.E.)
(Reference Category)			
Intercept 1		14.147	(0.017)***
Intercept 2		0.797	(0.300)
Intercept 3		0.042	(5.657)***
<u>Individual</u>	Sociodemographic Variables		
Age (16-30)	31-45	1.899	(0.025)***
	46-60	2.280	(0.021)***
	61-75	2.402	(0.033)***
	76 or above	2.472	(0.040)***
Gender (Male)	Female	1.306	(0.019)***
Employment Status (Employed)	Self-employed	0.810	(0.055)***
	Unemployed	0.535	(0.467)*
	Retired	0.877	(0.057)**
	Full-time Student	0.928	(0.070)
	Other Employment Status	1.496	(0.040)***
	Missing	1.099	(0.063)
Highest education level (Degree)	Other Higher Degree	0.978	(0.049)
	A-level or Equivalent	1.067	(1.491)
	GCSE or Equivalent	0.975	(0.046)
	Other Qualification	0.892	(0.044)**
	No Qualification	0.842	(0.049)***
	Missing	0.832	(0.063)***

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Variable	Category	OR	(S.E.)
(Reference Category)			
Ethnicity (White)	Mixed	0.894	(0.060)*
	Asian	0.868	(0.161)
	Black	0.944	(0.114)
	Other Ethnic Group	1.111	(0.070)
	Missing	0.867	(0.109)
Born in the UK (Yes)	No	0.968	(0.175)
	Missing	0.904	(0.176)
Individual monthly income	Log transformed income	1.433	(0.035)***
	Quadratic term of log transformed income	1.027	(0.097)
<u>Individual F</u>	Personal Value Variables		
Level of interest in politics	Fairly	0.943	(0.048)
(Very interest)	Not very	0.854	(0.056)***
	Not at all interested	0.730	(0.071)***
	Missing	0.844	(0.725)
Supported party (Conservative)	Labour	0.887	(0.045)**
	Liberal Democrat	1.115	(0.053)
	Scottish National Party	0.907	(0.114)
	Plaid Cymru	0.927	(0.183)
	Green Party	1.724	(0.047)***
	Ulster Unionist	1.080	(0.143)
	SDLP	0.767	(0.217)
	Alliance Party	1.222	(0.165)
	Democratic Unionist	1.028	(0.154)
	Sinn Fein	0.911	(0.197)
	Other party	0.970	(0.046)
	Cannot vote	0.893	(0.101)
	None	1.365	(0.056)***
	Missing	1.095	(0.051)
Voluntary work in the last 12 months	No	0.890	(0.037)***
(Yes)	Missing	0.884	(0.033)***
Donation to charity in the last 12	No	0.552	(1.091)
months (Yes)	Missing	0.943	(0.048)

Variable	Category	OR	(S.E.)
(Reference Category)			
<u>Individual Envir</u>	onmental Value Variables		
Environmental concern	Environmental Concern Score	1.062	(0.003)***
Believe in the effect of climate change in the UK (UK will not be affected in the next 30 and 200 years)	UK will only be affected in the next 30 years	1.238	(0.078)*
	UK will only be affected in the next 200 years	1.049	(0.051)
	UK will be affected in the next 30 and 200 years	1.205	(0.038)***
	Missing	1.469	(0.073)***
Believe green is an alternative living	Disagree	1.263	(0.021)***
style (Agree)	Missing	1.165	(0.115)
<u>Household Soc</u>	iodemographic Variables		
Ownership of car(s) (Yes)	No	1.189	(0.038)***
	Missing	1.053	(0.380)
Household	l Structure Variables		
Pensioner(s) in household (Yes)	No	0.919	(0.063)
Children aged 0-2 in household (Yes)	No	1.314	(0.047)***
Children aged 3-4 in household (Yes)	No	0.932	(0.066)
Children aged 5-11 in household (Yes)	No	0.980	(0.049)
Children aged 12-15 in household (Yes)	No	1.003	(0.052)
Household structure (Single household without children)	Single household with children	0.735	(0.117)***
	Non-single household without children	0.698	(0.081)***
	Non-single household with children	0.641	(0.118)***
Household Accommo	dation Characteristics Variable	<u>es</u>	
Tenure type (Home owned outright)	Home owned with mortgage	0.751	(0.056)***
	Home social rent	0.786	(0.066)***
	Home private/ employer rented	0.790	(0.071)***
	Other	1.394	(0.266)
	Missing	1.067	(0.147)
N · 11 1	1 11001110		
<u>Neighbourhood</u>	d Characteristic Variables		
Trash, junk and rubbish on the street in the neighbourhood (Yes)		1.276	(0.070)**

Variable	Category	OR	(S.E.)
(Reference Category)			
<u>Samplii</u>	ng Design Variables		
Sample composition (GPS)	Former BHPS	0.965	(0.042)
	EMBS	0.934	(0.080)
Government office region (North East)	North West	1.039	(0.115)
	Yorkshire and the Humber	1.126	(0.111)
	East Midlands	1.267	(0.099)
	West Midlands	1.129	(0.111)
	East of England	1.572	(0.077)***
	London	1.354	(0.089)*
	South East	1.597	(0.073)***
	South West	1.832	(0.069)***
	Wales	2.313	(0.055)***
	Scotland	0.869	(0.144)
	Northern Ireland	0.716	(0.202)*
Residential Area (Urban)	Rural	1.054	(0.036)

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Significant Individual-level Variables

The following individual-level variables are significant in explaining individuals' home-related behaviours: age, gender, marital status, employment status, monthly income, education level, whether or not born in the UK, level of interest in politics, affiliated political party, involvement in pro-social activities and environmental attitudes.

All five odds ratios for the age dummies are larger than one, implying that older people are more environmentally friendly in home-related behaviours than the younger generations. This result is consistent with previous hypothesis that there is a cohort effect in explaining conservation behaviours. According to Gifford and Nilsson (2014), those who have experienced wartime and post-wartime periods tend to engage in green conservation behaviours. Females are greener than males in terms of home-related environmentally behaviours. On the other hand, those who are currently in a marriage or cohabitation relationship behave more environmentally responsible than those who are not. There is no significant difference between the employed individuals and full-time students after controlling all the possible explanatory variables. However, self-employed are found to be less environmentally friendly than the employed, whereas those who have retired are more environmentally behaved. Individual income is also another important predictor for explaining individuals' behaviours. When an individual has a higher income, he or she is also more environmentally friendly in terms of their home-related behaviours. All odds ratios for the six education dummy variables are less than one, indicating that the less education

received by an individual, the less likely he or she is to behave environmentally at home. Again, ethnicity is not significant in explaining individuals' behaviours.

In terms of the level of interest in politics, those who are more interested in politics are greener than those who are not interested in politics. It can always be assumed that those who are interested in politics are more attached to the place where they are staying. Therefore, people tend to behave in a more appropriate way to protect the place that they are living. Labour Party supporters are less environmentally friendly than those who support the Conservative Party. This finding contradicts with some of the American studies which demonstrate the liberal supporters are more likely to engage in green behaviours than the conservatives (Feinberg and Willer, 2013; McCright and Dunlap, 2013). Nevertheless, the supporters of the Green Party are more likely to engage in home-related pro-environmental behaviours. On the other hand, people who are engaged to altruistic behaviours also participate in greener behaviours at home.

Unsurprisingly, those who have scored high in the environmental concern score are behaving greener in home-related behaviours. Moreover, those who believe the UK will be affected by climate change in the next 30 years or both 30 and 200 years tend to behave more appropriately at home as they are aware of the adverse consequences for not behaving environmentally friendly than those who do not believe in the consequences of climate change. People who are living green would not consider their living styles as an alternative. Only those who are not practicing green habits in their daily lives would consider green as an alternative living style. Therefore, it is not surprising to see that those who believe green is an alternative are acting not as green as those who do not think so.

Significant Household-level Variables

Ownership of car, presence of children below two years old in the household, household structure, tenure type, neighbourhood characteristics and residential areas are found to be significant in understanding individuals' home-related pro-environmental behaviours.

For home-related behaviours, those who are living in households without a car are more environmentally friendly than those who own a car in their households. Household structure, again, is another significant factor in explaining individuals' home-related environmentally friendly behaviours. Comparing with those who are living in a single household without any children, all other three household types (i.e., single household with children, non-single household without children and non-single household with children) are less environmentally responsible. Furthermore, those living with children below two years old are less environmentally friendly than those living without a child in this age group. This can be explained by the fact that a family living with very young children would not compromise

their children's benefits with good environment habits. As they put their children as the first priority, it explains why they would turn on the heating rather than putting more clothes on their children. Again, to further investigate the influence of household structures on the home-related behaviours, the population-average predicted probabilities are calculated. The predicted probabilities for four household structures are shown in Figure 3-3. As shown in the graph, the predicted probability for an individual from a single household without children to have high engagement in home-related environmentally friendly behaviours is the highest among all household structures.

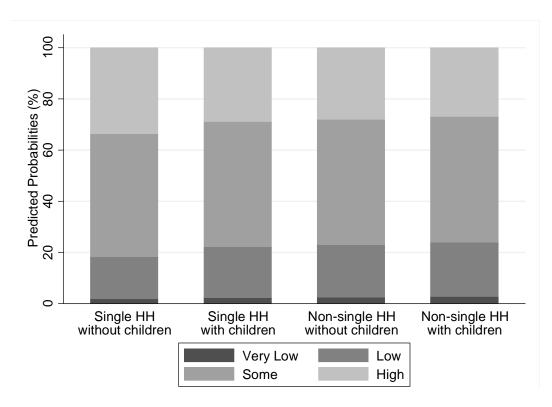


Figure 3-3 Population-Average Predicted Probabilities for Home-related Pro-Environmental Behaviour

For household accommodation characteristics, although the dwelling type is found not to be significant, tenure type remains significant in explaining individuals' home-related behaviours. Those who live in homes owned with a mortgage, social rent and private rent homes are less environmentally friendly than those who are living in homes owned outright. According to Utley and Shorrock (2006), energy efficiency measures vary across tenures. There is a lower proportion of social private rent homes with loft insulation installed than for homes owned outright. Therefore, it is not surprising to see that individuals living in social or private rent homes consume more energy as there are a high percentage of social and private rent homes without loft insulation.

Previous research has suggested that people who are living close to problematic sites tend to be more aware of the environmental problem and hence behave more environmentally friendly (Gifford and Nilsson, 2014). However, the result from this study shows a different result. Those who are living in a neighbourhood with cleaner streets are performing greener in home-related behaviours than those who live near to streets with trash, junk and rubbish.

There is a North-South difference when we focus on home-related behaviours. Those living in the East of England, London, South East and South West are more environmentally friendly than those living in the North East. People from Wales are also greener but the Northern Irelanders are not. Meanwhile, no urban-rural difference is observed.

3.4.3.3 OUTCOME 3 - Purchasing-related Pro-Environmental Behaviours

Table 3-13 presents the estimated odds ratios and the corresponding standard errors for the final cross-classified multilevel model on the purchasing-related environmentally friendly behaviours. Significant individual- and household-level covariates are then discussed.

Table 3-13 Estimated Coefficients for the Final Multilevel Cross-Classified Model: Outcome 3
- Purchasing-related Environmental Behaviours

Variable	Category	OR	(S.E.)
(Reference Category)			
Intercept 1		0.249	(1.003)***
Intercept 2		0.026	(9.748)***
Intercept 3		0.003	(83.170)**
<u>Individual S</u>	Sociodemographic Variables		
Age (16-30)	31-45	1.746	(0.026)***
	46-60	2.116	(0.022)***
	61-75	1.945	(0.039)***
	76 or above	1.662	(0.059)***
Gender (Male)	Female	1.464	(0.017)***
Employment Status (Employed)	Self-employed	1.046	(0.048)
	Unemployed	1.061	(0.059)
	Retired	1.159	(0.050)*
	Full-time Student	0.886	(0.076)
	Other Employment Status	1.235	(0.037)***
	Missing	0.232	(8.643)
Highest education level (Degree)	Other Higher Degree	0.856	(0.051)***
	A-level or Equivalent	0.706	(0.056)***
	GCSE or Equivalent	0.686	(0.059)***
	Other Qualification	0.647	(0.081)***
	No Qualification	0.645	(0.083)***
	Missing	0.783	(0.187)

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Variable	Category	OR	(S.E.)
(Reference Category)			
Ethnicity (White)	Mixed	0.789	(0.139)*
	Asian	1.164	(0.066)*
	Black	0.663	(0.144)***
	Other Ethnic Group	1.026	(0.166)
	Missing	0.934	(0.180)
Born in the UK (Yes)	No	1.682	(0.029)***
	Missing	0.931	(0.110)
<u>Individual P</u>	ersonal Value Variables		
Level of interest in politics (Very	Fairly	0.832	(0.054)***
interest)	Not very	0.722	(0.065)***
	Not at all interested	0.597	(0.086)***
	Missing	0.714	(0.861)
Supported party (Conservative)	Labour	1.154	(0.035)***
	Liberal Democrat	1.389	(0.041)***
	Scottish National Party	1.188	(0.087)
	Plaid Cymru	1.688	(0.097)**
	Green Party	2.623	(0.029)***
	Ulster Unionist	1.366	(0.116)*
	SDLP	0.969	(0.178)
	Alliance Party	1.750	(0.112)**
	Democratic Unionist	1.001	(0.163)
	Sinn Fein	0.965	(0.195)
	Other party	1.034	(0.045)
	Cannot vote	0.939	(0.110)
	None	0.943	(0.083)
	Missing	1.139	(0.049)*
Voluntary work in the last 12 months	No	0.776	(0.042)***
(Yes)	Missing	4.661	(0.493)
Donation to charity in the last 12	No	0.906	(0.034)**
months (Yes)	Missing	0.738	(0.885)
<u>Individual Envi</u>	ronmental Value Variables		
Environmental concern	Environmental Concern Score	1.077	(0.003)***
Believe green is an alternative living	Disagree	1.085	(0.025)**
style (Agree)	Missing	0.770	(0.184)
Thoughts about current lifestyle and	Would like to do bit more	1.180	(0.024)***
the environment (I'm happy with what I	Would like to do lots more	1.607	(0.038)***
do at the moment)	Missing	0.638	(0.827)

Category	OR	(S.E.)
ciodemographic Variables		
No	1.225	(0.036)***
Missing	0.557	(0.788)
d Structure Variables		
No	0.958	(0.060)
No	0.907	(0.066)
No	1.018	(0.060)
No	0.955	(0.051)
No	1.043	(0.051)
Single household with children	0.981	(0.087)
Non-single household without children	1.044	(0.040)
Non-single household with children	1.013	(0.065)
dation Characteristics Variabl	<u>es</u>	
Home owned with mortgage	0.903	(0.046)*
Home social rent	0.981	(0.054)
Home private/ employer rented	1.130	(0.049)*
Other	1.436	(0.237)
Missing	0.967	(0.159)
Semi-detached house/ bungalow	1.118	(0.036)**
End terraced/ terraced house/ bungalow	1.176	(0.037)***
Flat/ maisonette	1.204	(0.050)**
Others	1.022	(0.146)
Missing	1.267	(0.083)*
ng Design Variables		
Former BHPS	1.105	(0.037)*
EMBS	0.920	(0.081)
North West	0.939	(0.189)
Yorkshire and the Humber	1.010	(0.181)
East Midlands	1.102	(0.168)
West Midlands	0.947	(0.198)
	0.943	(0.188)
London	1.254	(0.139)
		(0.160)
		·)
South West	1.115	(0.173)
	iodemographic Variables No Missing d Structure Variables No No No No No Single household with children Non-single household with children Mon-single household with children dation Characteristics Variabl Home owned with mortgage Home social rent Home private/ employer rented Other Missing Semi-detached house/ bungalow End terraced/ terraced house/ bungalow Flat/ maisonette Others Missing g Design Variables Former BHPS EMBS North West Yorkshire and the Humber East Midlands West Midlands East of England	No 1.225 Missing 0.557 Structure Variables No 0.958 No 0.907 No 1.018 No 0.955 No 1.043 Single household with children Non-single household with children dation Characteristics Variables Home owned with 0.903 mortgage Home social rent 0.981 Home private/ employer 1.130 rented Other 1.436 Missing 0.967 Semi-detached house/ 1.118 bungalow End terraced/ terraced 1.176 house/ bungalow Flat/ maisonette 1.204 Others 1.022 Missing 1.267 g Design Variables Former BHPS 1.105 EMBS 0.920 North West 0.939 Yorkshire and the Humber 1.010 East Midlands 1.102 West Midlands 0.947 East of England 0.943 London 1.254

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Variable	Category	OR	(S.E.)
(Reference Category)			
	Scotland	0.867	(0.219)
	Northern Ireland	1.088	(0.185)
Residential Area (Urban)	Rural	1.116	(0.035)**

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

Significant Individual-level Variables

A range of individual sociodemographics and variables related to personal values and attitudes towards environmental issues are found to be significant in explaining individuals' purchasing-related pro-environmental behaviours. These individual sociodemographics include age, gender, employment status, education level, ethnicity and whether or not born in the UK. Meanwhile, significant variables related to personal values are level of interest in politics, affiliated political party and involvement in pro-social activities. Finally, the environmental concern score, belief on green is an alternative living style and thoughts about current lifestyle and the environment are the significant variables related to environmental attitudes.

Older people are more environmentally behaved when they are shopping as demonstrated by the odds ratios of all four age dummies. Compare to younger people, those who are over 31 years old are more likely to buy recycled paper products and are less likely to buy things with too much packaging. However, the age effect diminishes but remain significant for those who are aged 61 or above. Moreover, women tend to buy greener products (purchase green) than men. Those who have retired or are in the other employment status (other than self-employed, unemployed and student) also engage in greener purchasing behaviours than the employed. All five odds ratios of the education dummy variables are less than one and their magnitudes decrease as level of education decreases. This finding, again, shows that more educated people are more environmentally friendly in behaviours related to purchasing. Unlike the previous two behaviours (transport- and home-relate), ethnicity is an important explanatory variable in explaining purchasing-related environmental behaviours. Comparing to the reference group (the white community), those from black and mixed communities are less likely to purchase green. On the other hand, those who are born outside the UK but currently living here are more environmentally responsible.

Unsurprisingly, those who are less interested in politics tend to purchase less green products. Similar results are also observed in the previous two pro-environmental behaviours. Comparing to those who support the Conservative Party, the Labour Party, Liberal Democrat, Plaid Cymru, Green Party and Alliance Party supporters engage in greener purchasing-related behaviours. As expected, volunteers and charity donors are also greener when they shop.

People who score high in the environmental concern score are more likely to purchase green than those who score low. This is an expected result as those who are more concerned about the environments always behave appropriately to benefit the environment or reduce harm to the physical world. Those who disagree with the belief of green is an alternative living style tend to buy greener products than those who agree with such a belief. As pointed out in the previous section, only those who are not living green would consider such a living style as an alternative. Furthermore, it is not surprising to see that those who would like to do a little bit or a lot more to the environment also engage in more environmentally friendly purchasing-related behaviours.

Significant Household-level Variables

Ownership of car, household accommodation characteristics and residential area are the only significant household-level variables in explaining behaviours related to purchasing. Similar to the other two behaviours, individuals from households without a car are more likely to engage in greener purchasing-related behaviours. Furthermore, those living in homes owned with a mortgage tend to purchase less green products than those living in homes owned outright. However, those living in homes which are either private rent or employer rent show a reverse trend. In comparison, those living in detached houses, residents who are living in semi-detached houses, end-terraced houses and flats are more likely to purchase green. Finally, even though no North-South difference is observed, the rural residents are also more environmentally friendly than the urban counterparts when they shop.

Although some household-level variables are significant in explaining individuals' purchasing-related behaviours, it is surprising to see that variables related to household structure are all non-significant. The presence of pensioners or children below fifteen years old do not have any effect on individuals' behaviours. Moreover, there is no significant difference between the single householders and those who live with children or live in non-single households. It may be because unlike the home- and transport-related behaviours, purchasing behaviours are more personal and hence such behaviours are not easily influenced by people who are living together.

3.5 Conclusion

This paper aims to investigate the household, interviewer and geographical area effects on three different individuals' pro-environmental behaviours (transport-, home- and purchasing-related behaviours) and to examine the relationship between individuals' environmental attitudes and their behaviours. By adopting a cross-classified multilevel modelling approach, we successfully identify the role of household and separate the interviewer effect from the confounded area effect in three specific individuals' behaviours. Moreover, a positive relationship between individuals' environmental attitudes and environmental behaviours is also observed across these three behaviours.

Despite the nature of the environmentally friendly behaviours, household, interviewer and area random effects are all significant in explaining the individuals' environmental behaviours. The random specifications in the three final models show that the household play an important role in transport-, home- and purchasing-related behaviours. Although the magnitudes of both interviewer and area effects are relatively smaller than the household effect, they remain significant after accounting for the household effect.

In all three environmental behaviours being studied in this paper, household-level random effects contribute most among all random effects to explain the individuals' variation. The role of the household is able to explain 18.6%, 36.0% and 28.3% of the total individuals' variation for transport-, home- and purchasing-related behaviours respectively, which are very sizeable proportion. It is not too surprising to see that the household- random effect manages to explain a higher proportion of individuals' differences in the home-related behaviours than the transport-related one. This is because the individuals' home-related behaviours can be treated as an aggregated household behaviour. For example, people who are living in the same household may have consensus in whether or not to turn on the heating and it is not possible for a household member to turn on the heating in the house with another household member turning it off at the same time.

Based on the established theoretical framework and the results from the previous chapter, explanatory variables are included in the final models to explain individuals' green behaviours. The findings demonstrate a positive relationship between environmental attitudes and the three environmental behaviours. Most of the significant individual- and household-level variables are the same for the three behaviours, but some variables are different and some variables show a reversed effect, indicating small but key differences in the three behaviours. The variables that are significant in all three behaviours include age, employment status, education, whether or not born in the UK, level of interests in politics, affiliated political party, environment concern score, the belief in green is an alternative living

style, ownership of cars and tenure type. In general, those who receive more education, born outside the UK, have high interest in politics, have involvement in pro-social activities and live in households without a car are greener in all three behaviours. Interestingly, although age is significant in all three behaviours, the direction of effect in transport-related behaviours is different from that in the other two behaviours. Meanwhile, the effects of other variables vary across these behaviours. For instance, gender only appears significant in home- and purchasing-related behaviours, marital status is significant only in transport-related behaviour and ethnicity is significant in purchasing-related behaviours. Moreover, the North-South difference only exists in home-related behaviours only. Although the urban-rural difference can be observed in transport- and purchasing-related behaviours, results show that urban residents are less likely to travel green while they are more likely to purchase green than the rural counterparts.

The findings from this paper provide further evidence that there is a strong impact from the household on individuals' daily environmental behaviours, especially transport- and homerelated behaviours. Despite the nature of the behaviours, it is important for the UK government to consider the role of household when they want to promote environmentally friendly behaviours among general publics. It is also important to understand that different environmental behaviours can be affected and motivated by different individual- and household-level explanatory variables differently. Therefore, it is essential to understand the underlying factors when the government is trying to encourage different types of environmentally responsible behaviours.

There are some limitations in this study. Firstly, the UKHLS is not specifically designed to measure pro-environmental behaviours and environmental attitudes. As discussed in the first working paper (see Chapter 2), some important explanatory variables are omitted from the survey. The inclusion of the widely used New Ecological Paradigm Scale-Revised (Dunlap *et al.*, 2000) in the survey would be able to allow a valid measurement of environmental attitudes.

Secondly, the three outcome variables are only based on eleven pro-environmental behavioural items from the environmental behaviour module. Although the EFA has identified three dimensions from the eleven items and the CFA has confirmed the construct validity, the magnitudes of the factor loadings are still relatively small (see Table 3-3). In particular, the transport-related outcome consists of four items while the purchasing-related outcome consists of only two items. Brown (2015) argues that factors that are represented by two or three items may be underdetermined and highly unstable across replications. Therefore, the three dimensions being identified by the EFA in this study may be subjected to biases and errors, which will further compromise the validity of the model.

Thirdly, the current models for the three outcomes do not include any interaction term. Although no same-level and cross-level interaction terms are significant when we focus on the general pro-environmental behaviours in Chapter 2, we cannot simply assume these terms to remain insignificant for the three specific behaviours. However, due to the computational speed and other computing restriction, no interaction term has been included in the model.

Finally, since the three outcomes are modelled separately, relationships or correlations among these outcomes are not taken into consideration. Although preliminary finding has showed that there are weak correlations between the three behaviours (see Table 3-6 of Section 3.2.3), it may also be interesting to take the correlations into consideration. Therefore, further research could adopt a cross-classified multivariate multilevel modelling approach with the transport-, home- and purchasing-related behaviours as the multiple outcome variables. This allows all the outcome variables to be examined simultaneously. Moreover, such an approach can draw the conclusion about the correlations between the three outcomes and to test the magnitudes of all the explanatory variables on the multiple outcomes (Goldstein, 2011).

Chapter 4: Cross-National Comparisons of Environmental Behaviours – A Multilevel Modelling Approach (Paper 3)

4.1 Introduction

4.1.1 Background

There has been global cooperation in reducing greenhouse gas (GHG) emissions since the adoption of the Kyoto Protocol in 1997. Since then, there is an average of 5% emission reduction compared to the 1990 levels during 2008 to 2012 (United Nations Framework Convention on Climate Change, 2017a). In 2015, more than 140 nations have reached an agreement to tackle climate change and its consequences. The aim of the Paris Agreement is to increase global collaboration in keeping a global temperature rise below a certain threshold.

Climate change and the rise in average global temperature are directly contributed to by the increasing concentration of GHG in the earth's atmosphere. In response to the global threats posed by climate change, the United Nations Framework Convention on Climate Change suggests that there should be collective and global actions to reduce GHG emissions (United Nations Framework Convention on Climate Change, 2017b). All types of human activities are linked to the emissions of GHG, especially the activities in the industrial and energy industries. Moreover, individuals' daily actions and behaviours also increase the quantities of GHGs in the atmosphere. It is not only the responsibility at country or business levels to reduce emission of GHGs, individuals' efforts are equally important. At individual level, GHG emissions can be reduced by encouraging pro-environmental behaviours among people (Dietz et al., 2009; Fisher and Irvine, 2016). For example, The UK Energy Research Centre (2009) shows that changing the lifestyle of people in the United Kingdom can contribute to a 30% reduction of GHG emissions in the country. Everyone in the world contribute directly or indirectly to the GHG emissions and we are all affected by the negative impacts of climate change. Therefore, it is essential for all nations to work together to solve this global problem. The withdrawal of the United States from the Paris Agreement is expected to have wideranging consequences in reducing the global temperature rise to the targeted level. Hence, the need to reduce global GHG emissions becomes even more urgent.

Understanding how people behave in a particular country does not provide sufficient information to solve the problem of global climate change. We need to know how and why people from various countries behave in order to promote pro-environmental behaviours across the globe efficiently. There is an increasing need to examine the role of various personal characteristics on individuals' environmental behaviours, as well as how country-level variables influence people's behaviours.

Traditionally, research on pro-environmental behaviours has focused on one-country sample only (Oreg and Katz-Gerro, 2006). For studies that examine the underlying factors of environmental behaviours, most of them are again using data from a single sample that focuses on only one country or a single community (for example, Stern, 2000; Barr, 2007; Longhi, 2013; McCright and Dunlap, 2013; McCright, Xiao and Dunlap, 2014). Only over the last decade environmental behaviours and attitudes have been started to be investigated cross-culturally. However, the environmentalism literature is dominated by studies that explain cross-cultural differences in environmental attitudes (for example, Franzen and Meyer, 2010; Marquart-Pyatt, 2012b;a; Franzen and Vogl, 2013; Givens and Jorgenson, 2013; Fairbrother, 2016; Echavarren, 2017). Among cross-national studies on environmental behaviours, the majority of the literature focuses on public environmental behaviours, such as environmental activism or environmental movements (Dalton, 2005; Gillham, 2008; Freymeyer and Johnson, 2010). There are far fewer studies conducted on general environmental behaviours or specific personal (or private) behaviours. Duroy (2008) examine the country effect on two public environmental behaviours (signing petitions and donating money to environmental groups) and three personal environmental behaviours (recycling, saving water and buying household products) using single-level multivariate analysis. Meanwhile, Oreg and Katz-Gerro (2006) investigate one public behaviour and two personal behaviours (recycling, cut back on driving and environmental citizenship) using structural equation modelling (SEM). Although these studies focus on separate environmental behaviours, they do not take the multilevel nature of the data into consideration. On the other hand, there are some studies that focus on general proenvironmental behaviours. For instance, studies conducted by Hunter, Hatch and Johnson (2004) and, very recently, Pisano and Lubell (2017) examine how general public and private behaviours differ across countries. In particular, Pisano and Lubell (2017) use the 2010 Environmental module of the International Social Survey Programme to investigate both individual- and country-level factors on general public and private environmental behaviours. They adopt a multilevel modelling approach to investigate how personal psychosocial and country-level factors influence both types of behaviours, to compare the explaining power between individuals' sociodemographics and psychological factors and to examine the association between the strength of attitude-behaviour relationship and the

level of development of countries. However, their study does not distinguish between specific environmental behaviours. Steg, van de Berg and de Groot (2012) argue that different green behaviours are not necessarily correlated. Therefore, it is important to explore not just overall but also the different types of environmental behaviours in order to have a better picture of the roles of various individual- and national-level factors and to compare effects cross-nationally. Furthermore, since the resulting data has a complex structure, it is important to use appropriate data analyses techniques.

4.1.2 Aims and Methods

This paper investigates the cross-national differences in pro-environmental behaviours, identifies how different individual- and country-level factors influence individuals' behaviours and how the relationship between individual's environmental attitudes on behaviours varies across countries using a multilevel modelling framework.

The research aims of this paper are twofold: 1) to analyse the general pro-environmental behaviour and 2) to analyse four distinct behaviours: home-, recycling-, transport- and purchasing-related environmental behaviours. Although analysing general environmental behaviours allows us to understand how the effects of different underlying factors vary across individuals' overall behaviour, it does not take the complexity of human behaviour into consideration. Different types of pro-environmental behaviours are not necessarily correlated (Steg and Vlek, 2009) or could act in opposite directions. The previous chapter shows that different green behaviours can be influenced by different factors and in opposite directions. Therefore, it is important to investigate both the general behaviour and the specific types of behaviours. Meanwhile, environmental behaviour research mainly focuses on two directions: sociodemographics and social-psychological constructs (Dietz, Stern and Guagnano, 1998). As social-psychological constructs are more personal while sociodemographics can be personal (individual) or contextual (country), multilevel analysis does not only allow factors from both levels to be investigated simultaneously, but also allows the variations in the behaviour to be partitioned into personal- and country-levels.

The analysis is conducted on the 2010 Environmental module of the International Social Survey Programme (ISSP), a cross-national survey that mainly deals with environmental behaviours and attitudes towards environmental related issues (GESIS - Leibniz-Institut für Sozialwissenschaften, 2017). The dataset also contains a wide range of background variables (mostly sociodemographic variables) at individual level. In order to understand how country-level factors play an important role in explaining people's behaviours, information from other data sources, such as World Bank and World Economic Outlook, is also used in this study.

This paper consists of five main sections. The literature review section provides a comprehensive review on pro-environmental behaviours from a cross-national perspective. The data section describes the ISSP dataset and country-level variables. The methodology section discusses the multilevel modelling approach and the justification of the method. The result section presents the findings and provides a detailed interpretation of the final models. Finally, the paper ends with a conclusion by discussing the implication of this study and some recommendations for further research.

4.2 Data

4.2.1 Overview

This study uses data from the 2010 Environmental III module of the International Social Survey Programme (ISSP). The ISSP is an annually run cross-national survey with more than 50 participating countries, including major European countries, the United States, some Latin American, Asian and Oceania countries. Each year, the ISSP have different survey modules to address a wide range of important topics, such as environment, family and changing gender roles, health and social inequality. These survey modules are repeated over years, allowing research to be conducted from both cross-time and cross-national perspectives.

In particular, the Environmental module is conducted in 1993, 2000 and 2010. This module contains questions on environmental behaviours and attitudes, as well as respondents' opinions on different environmental issues and their views on their governments' measures on environmental protection. In the latest survey which is carried out in 2010, a total of 36 countries have implemented the Environmental module and there are more than 50,000 respondents across these countries.

4.2.2 Survey Design and Data Collection

In ISSP, each country funds and organises their own surveys. Therefore, survey designs, sampling methods and modes of data collection vary across countries. In order to ensure data quality, the ISSP committee set up procedures for conducting surveys and archiving data and they also ensure surveys are conducted in accordance to their working principle (GESIS - Leibniz-Institut für Sozialwissenschaften, 2017; ISSP Research Group, 2017).

In the 2010 Environmental module, each country implements the questionnaires in their own ways. Some of the participating countries include the module in their national surveys, while some field the module as an individual survey. Sampling procedures are different depending on the country. The most common sampling method is stratified multi-stage sampling. Data

collection mode also varies. Among all 36 countries, 20 of them use face-to-face interviews, five countries use self-completion questionnaires while the remaining eleven adopt a mixed mode approach. Dependent on the sampling methods and modes of data collection, most countries start with an initial sample of approximately 3,000 addresses. The average response rate is 57.0%. Most of the countries conduct the surveys between 2010 and 2011, with the exception from Australia, Iceland, Portugal and Slovak Republic. For non-English speaking countries, questionnaires are translated into local languages. In countries with multi-ethnics groups, questions are translated into more than one language. Sampling weights are included in 22 countries¹. More information regarding the survey design, data collection, sample size, response rate and date of fieldwork is provided in the Appendices C.1 and C.2.

4.2.3 Analysis Sample and Study Population

The dataset contains data of 50,551 individuals coming from 36 countries: Argentina (AR), Australia (AU), Austria (AT), Belgium (BE), Bulgaria (BG), Canada (CA), Chile (CL), Croatia (HR), Czech Republic (CZ), Denmark (DK), Finland (FI), France (FR), Germany (DE), Iceland (IS), Israel (IL), Japan (JP), Republic of Korea (KR), Latvia (LV), Lithuania (LI), Mexico (MX), Netherlands (NL), New Zealand (NZ), Norway (NO), Philippines (PH), Portugal (PT), Russian Federation (RU), Slovakia (SK), Slovenia (SI), South Africa (ZA), Spain (ES), Sweden (SE), Switzerland (CH), Taiwan (TW), Turkey, (TR) United Kingdom (GB) and the United States (US). Among these 36 countries, three countries are excluded from the analysis. Since some of the national-level data are not available for Taiwan while one question which is used to derive an explanatory variable is not asked in Turkey, we do not consider these two countries in our analysis. Since the ISSP Methodology Committee initially rejected the Iceland data for methodological reasons (ISSP Research Group, 2012), we exclude the Iceland dataset as we are unsure of its validity. After removing data from the above three countries, a total of 45,765 individuals remain in the final dataset. In order to preserve a constant analysis sample size throughout the modelling process, multiple imputation is conducted to impute missing items across the variables using the package mice 2.9 (van Buuren and Groothuis-Oudshoorn, 2011) in R (R Core Team, 2016). The package mice 2.9 imputes data by chained equations, which is also referred to as imputation using chain equations or full conditional specification (Carpenter and Kenward, 2013). The imputation process is implemented separately for each

¹ The following countries provide weights in the data: Australia (AU), Austria (AT), Belgium (BE), Bulgaria (BG), Canada (CA), Chile (CL), Czech Republic (CZ), Finland (FI), France (FR), Germany (DE), Lithuania (LI), Mexico (MX), Netherlands (NL), New Zealand (NZ), Philippines (PH), Portugal (PT), Russian Federation (RU), Slovakia (SK), South Africa (ZA), Spain (ES), United Kingdom (GB) and the United States (US)

country. After the imputation procedure, the completed data of 45,765 individuals from 33 countries is merged with country-level data obtained from other sources.

This study uses a model-based approach to analyse the completed data. Sampling weights are not included in the analysis. The debate on whether a design-based or a model-based analysis should be adopted has been discussed in Section 1.5.3.2 of Chapter 1. We acknowledge the role of weights in analysing cross-country survey data from the design-based approach, yet, unweighted analysis can also effectively produce unbiased estimates and inferences (Snijders and Bosker, 2012). In the ISSP, it is assumed that the 33 countries are samples from a superpopulation. According to Kaminska and Lynn (2016), we can view this cross-country sample as a multiple-frame sample. Hence, there are 33 sampling frames to represent the superpopulation. In such a case, these frames can be treated as strata (Hartley, 1962). Here, the clustering nature of the sample design can be accounted for by the proposed modelling approach (i.e., multilevel modelling framework). Details about the methodology are discussed in Section 4.3. The population target of inference is all people who are 16+ living in all countries presented by the sample. Since the 33 countries in the data is a finite sample from an infinite population, the proposed multilevel model holds for the superpopulation. As a result, the inferences from an unweighted analysis can be generalised to the countries represented by the sample.

4.2.4 Response Variable

General Pro-Environmental Behaviour Score

In the Environmental module, there are six questions related to environmental behaviours and they are listed in Table 4-1. For each of these items, respondents are asked to indicate how often they behave accordingly. Possible answers are "always", "often", "sometimes" and "never".

Table 4-1 List of Pro-Environmental Behaviours in 2010 ISSP Environmental Module

- 1 Sort glass or tins or plastic or newspapers and so on for recycling
- 2 Buy fruit and vegetables grown without pesticides or chemicals
- 3 Cut back on driving car for environmental reasons
- **4** Reduce the energy or fuel you use at home for environmental reasons
- **5** Choose to save or re-use water for environmental reasons
- **6** Avoid buying certain products for environmental reasons

A reliability test is conducted on these items, showing high internal reliability and consistency (Cronbach's alpha = 0.752). As high Cronbach's alpha indicates the items are measuring the same underlying concept, we are able compute an overall score of general proenvironmental behaviours by summing up the answers of these items. Responses to these six

items are recoded to range between zero and three where 0 = never, 1 = sometimes, 2 = often and 3 = always. Then, an additive measure for general pro-environmental behaviour is created. It ranges from zero to 18 with a higher score indicating more environmentally friendly in daily living. The distribution of this measure based on 45,765 individuals is presented in Figure 4-1, which approximately follows a normal distribution with mean = 7.99, standard deviation = 4.01 and median = 8.00. Meanwhile, the distributions of the measure based on each country are shown in Figure 4-2.

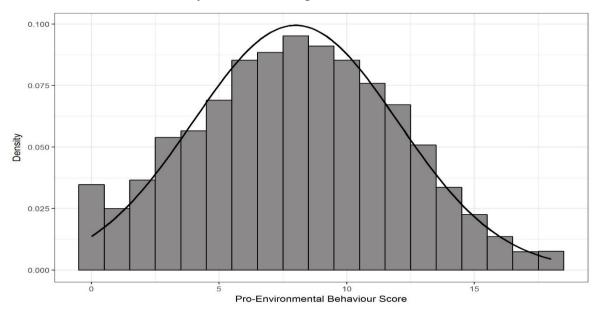


Figure 4-1 Distribution of the Measure of General Pro-Environmental Behaviour

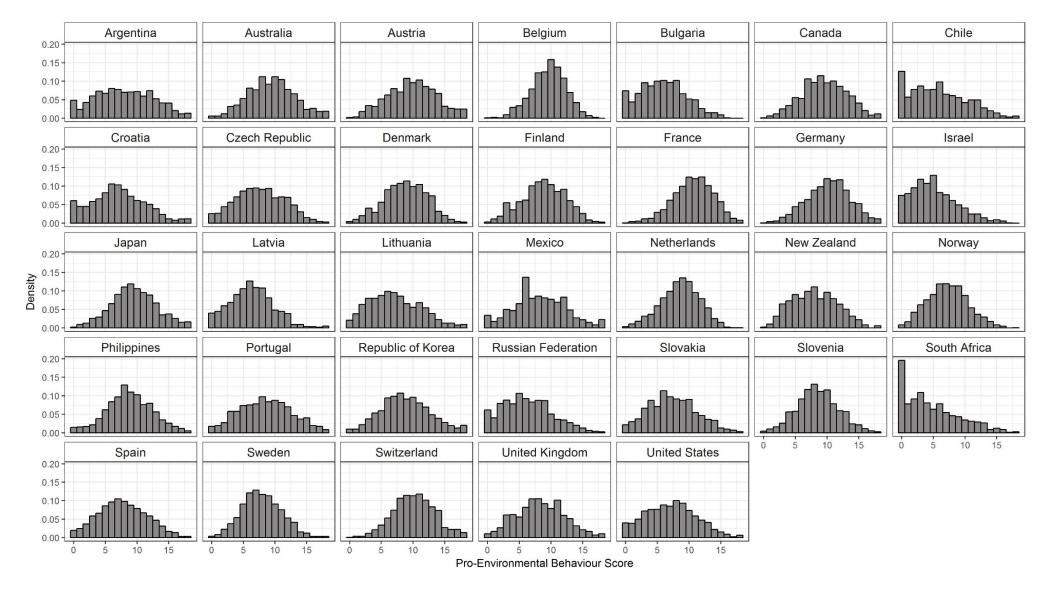


Figure 4-2 Distributions of the Measure of General Pro-Environmental Behaviour by Countries

Four Specific Pro-Environmental Behaviours Scores

A further focus of this study is to investigate how different individual- and country-level variables influence different types of environmental behaviours. Unlike the first measure of general pro-environmental behaviour, we break down the aggregated score into multiple scores for further investigation. Explanatory factor analysis (EFA) is first conducted on the six items to identify the factor structure of environmental behaviours. Preliminary results suggest that there are two distinct factors: the first factor identifies home-related behaviour (reduce energy or fuels and save or re-use water) and the second factor distinguishes purchasing-related behaviour (buy fruits without pesticides and avoid buying certain products). The factor loadings of these four items range from 0.460 to 0.808 and they are all statistically significant at the 1% level. However, the remaining two items (cut back on driving and sort glass, tins, plastics and newspapers) do not load on any common factor. As these items are ordinal, we compute the Spearman's rank order correlation (or the Spearman's rho correlation) to examine the strength of the relationship (see Table 4-2). It is a non-parametric correlation for ordinal variables (Chen and Popovich, 2002). As shown in the table, the correlations between the first item (sort glass, tins, plastics and newspaper) and the remaining five items are weak. Similar results can also be observed between item 3 (cut back on driving) and other items. Therefore, it is unsurprisingly that neither of these two items can be loaded onto a common factor in the EFA. As items 1 and 3 are relatively uncorrelated to other items, we treat them as two separate environmental behaviours: recycling- and transport-related.

Table 4-2 Spearman's Rho Correlation between Six Pro-Environmental Behaviour Items

	1	2	3	4	5	6
1 Sort glass, tins, plastics & newspapers	1.000					
2 Buy fruits without pesticides	0.241	1.000				
3 Cut back on driving	0.217	0.283	1.000			
4 Reduce energy or fuels	0.340	0.294	0.405	1.000		
5 Save or re-use water	0.284	0.254	0.316	0.540	1.000	
6 Avoid buying certain products	0.316	0.441	0.343	0.470	0.464	1.000

Note: all correlations are statistically significantly at 1%.

Based on the result from the above EFA and correlations, we create measures for four specific types of pro-environmental behaviours. These measures are four indexes which are derived from the raw scores of the corresponding environmental behaviours.

The raw scores of home-related behaviour is the sum of items 4 and 5. Similarly, we sum up items 2 and 6 to create the raw score of purchasing-related behaviour. Both of these raw scores ranged from zero to six. Meanwhile, as transport- and recycling-related behaviours

contain only one item each, their raw scores are based on the respective items (transport-related: item 3 and recycling-related: item 1). After obtaining the raw score for each of the specific behaviours, we convert the raw score into a three-point-scale index, ranging between one and three: 1 = low participation; 2 = some participation; and 3 = high participation. For both home- and purchasing-related behaviours, we recode 0, 1 to 1 (= low participation); 2, 3 to 2 (= some participation) and 4, 5, 6 to 3 (= high participation). The frequencies of the derived ordinal outcome variables are presented in Table 4-3 while their distributions are shown in Figure 4-3.

Table 4-3 Frequencies of the Four-specific Pro-Environmental Behaviours

	Но	Home		Purchasing		Recycling		Transport	
	N	%	N	%	N	%	N	%	
Low	12,746	27.85	14,383	31.43	14,146	30.91	17,393	38.01	
Some	18,135	39.63	19,681	43.00	9,814	21.44	15,514	33.90	
High	14,884	32.52	11,701	25.57	21,805	47.65	12,858	28.10	
Total	45,765	100.00	45,765	100.00	45,765	100.00	45,765	100.00	

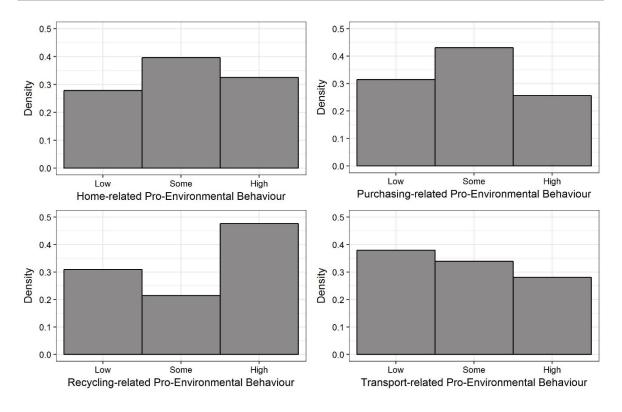


Figure 4-3 Distributions of the Four-specific Pro-Environmental Behaviours

In order to examine the relationships between these ordinal outcomes, we compute the Spearman's rank order correlation. Table 4-4 shows the Spearman's rho correlations among home-, purchasing-, recycling- and transport-related behaviours. Home-related behaviour is relatively correlated to purchasing-related behaviours. However, there are only modest correlations between recycling and the other three behaviours. Again, this further confirms with the previous chapter that behaviours are not necessarily correlated with each other.

Table 4-4 Spearman's Rho Correlations between the Four-specific Pro-Environmental Behaviours

	Home	Purchasing	Recycling	Transport
Home	1.000			
Purchasing	0.442	1.000		
Recycling	0.322	0.286	1.000	
Transport	0.396	0.351	0.214	1.000

Note: all correlations are statistically significantly at 1%.

4.2.5 Individual-Level Explanatory Variables

As discussed in the literature review, sociodemographics, personal values and environmental attitudes at individual-level are all associated with personal environmental behaviours.

Therefore, we include all relevant variables that are available in the ISSP data in our analysis.

Sociodemographics

Sociodemographic variables include: gender (male and female), age group (15-30, 31-45, 46-60, 61-75 and 76-99), employment status (employed, unemployed, student, retired, homemaker and other), highest education level (no formal qualification, lowest qualification, intermediate secondary completed, higher secondary completed, university degree, uncompleted and university degree completed), marital status (married or cohabitation, currently not married and never married), self-rated social status (a scale between one and ten, where 1 = lowest and 10 = highest), household size (1-person, 2-person, 3-person, 4-person and more-than-5-person households) and area of residency (city, small city and rural).

Personal Values

We also include variables that can be used to describe personal values: *religion* (with and without a religion), *voting history in last election* (yes, no and not eligible to vote), *political orientation* (far left, left/ centre left, centre/ liberal, right/ conservative and far right), left-right ideology, post-materialistic value as well as social and political trusts.

Left-Right Ideology is measured by two items which are listed in Table 4-5. Respondents are asked to express their agreement or disagreement on these statements using a five-point Likert scale. As the correlation between them is weak (Spearman's rho correlation = 0.086), we use them as two separate items rather than creating an additive measure.

Table 4-5 Measure of Left-Right Ideology

- 1 Private enterprise is the best way to solve (respondent's country's) economic problems
- 2 It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes

For the measure of *Post-Materialistic Value*, we derive a post-materialism index using the 4-item battery developed by Inglehart (1990;(1997). Respondents are asked to pick their top two priorities from the items in Table 4-6 that they consider are important for their countries to do. The measure ranges between zero and two: 0 = post-materialistic, 1 = neutral, 2 = materialistic. If the respondents choose items 1 and 3, we code them as materialist. Meanwhile, those who choose items 2 and 4 are coded as post-materialist. Finally, we code those who pick either items 1 or 3 with either items 2 or 4 as neutral (neither post-materialistic nor materialistic).

Table 4-6 Measure of Post-Materialistic Value

- **1** Maintain order in the nation
- **2** Give people more say in government decisions
- **3** Fight rising prices
- 4 Protect freedom of speech

Social and Political Trusts are measured by four items which are listed in Table 4-7. We derive a measure of social trust by summing up the first two items (Spearman's rho correlation = 0.546). Meanwhile, the measure of political trust is calculated by adding up items 3 and 4 (Spearman's rho correlation = 0.370). Both measures range between zero and eight, with higher value indicating higher level of trust.

Table 4-7 Measure of Social and Political Trust

- 1 Most people can be trusted, or that you can't be too careful in dealing with people
- 2 Most people would try to take advantage of you if they got the chance, or they would try to be fair
- 3 Most of the time we can trust people in government to do what is right
- 4 Most politicians are in politics only for what they can get out of it personally

Environmental Values

Environmental attitudes are measured by a range of questions (see Table 4-8). Previous research has successfully identified different latent constructs related to environmental attitudes, concerns and knowledge from these questions (Franzen and Meyer, 2010; Marquart-Pyatt, 2012a;2015; Pisano and Lubell, 2017). We first perform an EFA on these 23 items and results show that there is a five-factor structure. Afterwards, we apply a five-factor CFA on the pooled analysis sample (N = 45,765) using the R package "lavaan" (Rosseel, 2012). The overall model fit statistics are: $\chi^2(216) = 19,792.035$, p=0.000; CFI = 0.929; SRMR =

0.047 and RMSEA = 0.045. Since the sample size of the data is large, a chi-square test is very likely to give statistically significant results. However, other model fit statistics (i.e., CFI, SRMR and RMSEA) show a good fit of model (Hu and Bentler, 1999; Fan and Sivo, 2005). All standardised factor loadings are statistically significant at 0.01 level, ranging between 0.330 and 0.890. These five dimensions are: environmental risk perception, environmental attitude, attitudes towards environment and modern life, environmental knowledge and willingness to make personal sacrifice for the environment. We then derive five additive measures for these dimensions.

Environmental Risk Perception includes seven items which present the awareness of potential negative consequences to the environment from human's activities. Respondents are asked how dangerous they think seven types of problems caused by human on the environment are (see items 1 – 7 in Table 4-8). Possible answers are: extremely dangerous, very dangerous, somewhat dangerous, not very dangerous and not dangerous at all. The Cronbach's alpha of these seven items is 0.810, indicating very high internal consistency. These seven items are recoded to range between zero and four where larger values indicate more awareness of the negative consequences of human activities on the environment. The measure of environmental risk perception is then derived by summing up all seven items.

The next measure is *Environmental Attitude* which contains seven items that measure individuals' self-belief in influencing and solving environmental problems. Respondents are asked to express their agreement on seven statements (see items 8 – 14 in Table 4-8) from a 5-point Likert scale. There is a high internal consistency among these seven items (Cronbach's alpha = 0.737). Responses to these seven items are recoded so that larger values indicate higher self-efficacy. Afterwards, the measure of environmental attitude is calculated by summing up all seven items.

Attitudes towards Environment, Science and Economic Growth is a latent construct that comprises four items (items 15 – 18 of Table 4-8). These items reflect how respondents perceived the relationships between environment and modern life. Respondents are asked to express their agreement or disagreement with these items using a 5-point Likert scale. The Cronbach's alpha of these four items is 0.571, showing an acceptable internal consistency. We then sum up all four items to derive the measure for attitudes towards the environment, science and economic growth. Higher values indicate a more positive attitude towards the effect of modern technology on the environment.

Environmental Knowledge contains two items which ask the respondents to self-report their familiarity to the causes and solutions of environmental problems (items 19 and 20 from Table 4-8). Respondents are asked to answer how much they feel they know about these

issues on a 5-point scale ranging between 0 = know nothing at all to 4 = know a great deal. These two items are highly correlated (Spearman's rho correlation = 0.666). The measure of environmental knowledge is then derived by adding up the responses of these two items.

Willingness to Make Personal Sacrifice for Environment is a latent construct which consists of three items that respondents would compromise in order to protect the environment from a 5-point scale. These three items (Items 21 - 23) are listed in Table 4-8 with Cronbach's alpha = 0.837, indicating a high internal consistency. We create the measure for willingness to make a sacrifice for the environment by summing up these three items.

Table 4-8 Measure of Environmental Attitudes, Concerns and Knowledge

- **1** Air pollution caused by cars
- **2** Air pollution caused by industry
- 3 Pesticides and chemicals used in farming
- 4 Pollution of (respondent's) country's rivers, lakes and streams
- **5** A rise in the world's temperature caused by climate change
- **6** Modifying the genes of certain crops
- 7 Nuclear power stations
- **8** We worry too much about the future of the environment and not enough about prices and jobs today
- **9** People worry too much about human progress harming the environment
- **10** It is just too difficult for someone like me to do much about the environment
- 11 There are more important things to do in life than protect the environment
- 12 There is no point in doing what I can for the environment unless others do the same
- 13 Many of the claims about environmental threats are exaggerated
- 14 I find it hard to know whether the way I live is helpful or harmful to the environment
- 15 We believe too often in science, and not enough in feelings and faith
- 16 Overall, modern science does more harm than good
- 17 Almost everything we do in modern life harms the environment
- **18** Economic growth always harms the environment
- **19** Know about the causes of environmental problems
- **20** Know about the solutions to environmental problems
- **21** Pay much higher prices
- **22** Pay much higher taxes
- 23 Accept cuts in standard of living

Meanwhile, *Environmental Justice* is measured by two items (see Table 4-9). Initially, these two items are also included in the EFA. However, none of them load on any factor. Therefore, we include them as separate measures. These items reflect how respondents feel about climate justice and international environmental collaboration (Çarkoğlu and Kentmen-Çin, 2015). Since the correlation between both items is weak (Spearman's rho correlation =

0.042), we use them as two separate measures. Both items are recoded to range between zero and four where a larger value indicates higher perceived environmental justice.

Table 4-9 Measure of Environmental Justice

- 1 For environmental problems, there should be international agreements that (respondent's country) and other countries should be made to follow
- 2 Poorer countries should be expected to make less effort than richer countries to protect the environment

4.2.6 Country-Level Explanatory Variables

At the country level, we include seven economic-and-education-development-related, four environments-related, two demographic-related and three political-related variables.

Otherwise specified, these measures are based on 2010 data.

We use the Gini coefficient (United Nations Development Programme, 2010), per capita GDP in purchasing power parity (GDP PPP; International Monetary Fund, 2010), Corruption Perceptions Index (CPI; Transparency International, 2010), the country's average postmaterialism index which is derived from the individuals' index and Education Index from the Human Development Report 2013 (United Nations Development Programme, 2013), the Human Development Index (HDI; United Nations Development Programme, 2010) and overall life satisfaction (United Nations Development Programme, 2011) to measure economic and education development. In order to measure environmental quality and conditions, we use the Environmental Performance Index (EPI; Hsu et al., 2014) from the Yale Center for Environmental Law & Policy and three indicators which measure the percentages of people in the population who are satisfied with air quality, water quality and government actions in preserving the environment from 2011 Human Development Report (United Nations Development Programme, 2011). Meanwhile, two demographic-related measures are obtained from the United Nations: population density (United Nations, 2015) and percentage of population living in urban areas (United Nations, 2014). We also use the percentage of people who voiced opinion to public officials (United Nations Development Programme, 2010) as a measure of political engagement. Finally, country's average social and political trusts which are derived from the individuals' data are also included as political-related variables.

4.3 Methodology

4.3.1 A Multilevel Modelling Framework

A traditional analysis approach assumes observations to be independent of each other. However, this assumption is not valid for cross-country data as individuals in the data are clustered (or grouped) in countries. As there are institutional and cultural differences between countries, we expect individuals from the same country to be more similar to each other than to individuals from another country. In this case, the assumption of independence of observation is violated and hence underestimating the standard errors and producing wrong statistical inferences (Snijders and Bosker, 2012). In order to account for the clustering nature of data, we adopt a multilevel modelling approach in this paper.

Multilevel modelling is a common approach to analyse clustered data. It includes random error terms in a standard regression model to account for the clustering structure. Moreover, it treats the hierarchical structure as a central part of the analysis and allows the variation in the outcome variable to be partitioned into between- and within-group sources.

Consequently, it identifies how the total variation is contributed to the different level effects (Goldstein, 2011). In our case, we are seeking to partition the total variation into between-country and between-individual (or within-country) variance. In additions, multilevel modelling also allows us to include explanatory variables at different levels and cross-level interactions to the model simultaneously without the loss of information and the risk of the ecological fallacy. Therefore, we can include both individual- and country-level variables in the analysis using multilevel modelling.

The simplest case of a multilevel model is the *random intercept model*. The model contains two components: a fixed part and a random part (Snijders and Bosker, 2012). The fixed part specifies the relationship between the mean of the outcome variable and explanatory variables while the random part contains residuals at all levels. In a random intercept model, the relationships between the explanatory variable and the outcome variable are assumed to be identical for all clusters (Snijders and Bosker, 2012). However, this assumption is not always true. It is possible that the effect of an explanatory variable of an individual is stronger in some groups than in others. The assumption of the random intercept model can be relaxed by allowing such effects to vary across group, leading to a *random slope model* (also known as a *random coefficient model*). As one of the aims of this paper is to examine how the effect of individuals' environmental attitudes on pro-environmental behaviours varies across nations, a random slope modelling approach is adopted in this paper to allow environmental attitudes to have a different effect on behaviours for each country.

There are five outcome variables in this paper. Four of them are ordered categorical outcome with three categories (see Figure 4-3). Treating ordinal categorical data as continuous data in analysis can lead to a severe downward bias (Hox, 2010). In order to avoid the possible bias, we use generalised linear models to analyse ordered categorical data as they are specifically designed for this type of data. Goldstein (2011) extends the generalised linear model to handle ordered responses which are hierarchical in nature. Therefore, a multilevel random slope cumulative ordered logit modelling approach will be used for the four ordinal outcomes while the multilevel random slope modelling approach will be adopted for the continuous outcome.

4.3.2 Model Specification

Multilevel Random Slope Model

Let y_{ij} denote the continuous outcome variable of interest (i.e. the general pro-environmental behaviour score) for individual i from country j. The general form of the multilevel random slope model is:

$$y_{ij} = \beta_0 + \mathbf{\beta}_1^{\mathrm{T}} \mathbf{X}_{ij} + u_{0j} + u_{1j} \mathbf{Z}_{ij} + e_{ij}$$

where \mathbf{X}_{ij} is a vector of individual- and country-level covariates; β_0 is the overall intercept in the linear relationship between the dependent and independent variables specified in the model, $\boldsymbol{\beta}_1$ is the average slope for the independent variables \mathbf{X}_{ij} across all countries (sometimes known as grand mean slope) and \mathbf{Z}_{ij} is an individual-level covariate with a random slope where \mathbf{Z}_{ij} is an element of \mathbf{X}_{ij} (i.e. $\mathbf{Z}_{ij} \in \mathbf{X}_{ij}$). The parameter e_{ij} is the random effect term for the individual-level and is assumed to follow a normal distribution with zero mean and variance $\sigma_e^2 : e_{ij} \sim \mathbf{N}(0, \sigma_e^2)$. The parameters u_{0j} and u_{1j} are the random intercept and random slope at country-level respectively. Both of them are assumed to follow a bivariate normal distributions with zero means, variance σ_{0u}^2 and σ_{1u}^2 respectively and covariance $\sigma_{u01} : u_{0j} \sim \mathbf{N}(0, \sigma_{0u}^2)$, $u_{1j} \sim \mathbf{N}(0, \sigma_{1u}^2)$ and $\mathbf{cov}(u_{0j}, u_{0j}) = \sigma_{u01}$. These two country-level random effect terms are usually correlated. The term $u_{1j}\mathbf{Z}_{ij}$ can be regarded as a random interaction term between country and \mathbf{Z}_{ij} .

At each hierarchical level, the corresponding Variance Partitioning Coefficient (VPC) can be calculated to measure the proportion of total variance that is contributed to the differences between individuals and countries. The VPCs for individual and country-level are:

$$\text{VPC}_{\text{individual}} = \frac{\text{between individual variation}}{\text{total variation}} = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_{u0}^2 + 2\sigma_{u01}Z_{ij} + \sigma_{u1}^2Z_{ij}^2}$$

$$\text{VPC}_{\text{country}} = \frac{\text{between country variation}}{\text{total variation}} = \frac{\sigma_{u0}^2 + 2\sigma_{u01}Z_{ij} + \sigma_{u1}^2Z_{ij}^2}{\sigma_e^2 + \sigma_{u0}^2 + 2\sigma_{u01}Z_{ij} + \sigma_{u1}^2Z_{ij}^2}.$$

In the random slope model, the country-level variance is a function of the covariate (Z_{ij}) that has a random slope at country-level. Therefore, the variance at country-level is a quadratic function of the specific explanatory variables.

Multilevel Random Slope Cumulative Ordered Logit Model

Let y_{ij} denote the ordinal outcome variable of interest (i.e., the four specific proenvironmental behaviour scores) for individual i from country j. The outcome variable is a three-point-scale index, which takes three-response categories c=1,2,3, where a larger value indicates the individual are more environmentally friendly in their daily behaviours. In an ordinal multilevel model, a single vector of regression coefficients is estimated, since the effect of the explanatory variables is assumed to be the same irrespective of the category, c, being considered. Therefore, the general form of the multilevel random slope cumulative ordered logit model is written as:

$$\log \left[\frac{\Pr(y_{ij} \le c)}{\Pr(y_{ij} > c)} \right] = \alpha_c - \left(\boldsymbol{\beta}^{\mathrm{T}} \mathbf{X}_{ij} + u_{0j} + u_{1j} \mathbf{Z}_{ij} \right), \quad c = 1, 2$$

where \mathbf{X}_{ij} is a vector of individual- and country-level covariates and interactions; $\boldsymbol{\beta}$ is a vector of coefficients for the covariate variables \mathbf{X}_{ij} while \mathbf{Z}_{ij} is an individual-level explanatory variable from the vector \mathbf{X}_{ij} that has a significant variance component between countries and α_c is the threshold parameter, representing the intercepts in the linear relationship between the log-odds of a response of $c \leq 2$ and the predicted variables specified in the model. The intercepts are ordered with $\alpha_1 \leq \alpha_2$ because the cumulative response probability increases with the number of categories of the response. In the model, the effects of the covariates are assumed to be constant for all categories on the logarithmic scale. This is known as the proportional odds assumption. Under this assumption, the effects of covariates are the same when c = 1 is compared versus c = 2, 3 and c = 1, 2 is compared versus c = 3.

The parameters u_{0j} and u_{1j} are the random effect terms at country-level and they are assumed to follow a bivariate normal distribution with zero means, variances σ_0^2 and σ_{1u}^2 respectively, and covariance σ_{u01} . The term $u_{1j}Z_{ij}$ has the same interpretation as in the multilevel random slope model for continuous outcome as discussed above. In the logit model, the linear relationship between the covariates and the corresponding log-odds for country j is $\beta_Z + u_{1j}$, where β_Z is the fixed effect for Z_{ij} .

The multilevel random slope cumulative ordered logit model can be written as a linear model in terms of latent continuous variable y_{ij}^* which underlies the observed ordinal variable y_{ij} (Snijders and Bosker, 2012). The relationship between the observed and the unobserved outcome variables is defined as:

$$y_{ij} = \begin{cases} 1, & \text{if } y_{ij}^* \le \alpha_1 \\ 2, & \text{if } \alpha_1 < y_{ij}^* \le \alpha_2 \\ 3, & \text{if } \alpha_2 < y_{ij}^* \end{cases}$$

where $\alpha_1 \leq \alpha_2$ are the threshold parameters to be estimated.

Then, a linear regression model for the latent (or unobserved) variable y_{ij}^* can be defined as:

$$y_{ij}^* = \mathbf{\beta}^{\mathrm{T}} \mathbf{X}_{ij} + u_{0j} + u_{1j} \mathbf{Z}_{ij} + e_{ij}^*$$

where e_{ij}^* is the latent individual-level error random term in the linear regression model while u_{0j} and u_{1j} are the random intercept and random slope for country-level respectively. The parameter e_{ij}^* is assumed to follow a standard logistic distribution with zero mean and variance σ_e^* , where $\sigma_e^{*2} = \pi^2/3 \approx 3.29$. The scale of this error term is a fixed constant as y_{ij}^* is a latent variable.

There are various methods to calculate the VPC for multilevel random slope cumulative ordered logit models (Goldstein, 2011). These methods include model linearisation, simulation, binary linear model and latent variable approaches. In particular, the latent variable approach is the most common way to calculate the VPC.

According to the latent variable approach, the total variance is obtained by summing up the levels one and two variances. As the country-level variance is a quadratic function of the specific explanatory variables, the total variance is expressed as:

Total Variance =
$$\sigma_e^{*2} + \sigma_{u0}^2 + 2\sigma_{u01}Z_{ij} + \sigma_{u1}^2Z_{ij}^2$$
.

Therefore, the country-level VPC can be written as:

$$\text{VPC}_{\text{country}} = \frac{\text{between country variation}}{\text{total variation}} = \frac{\sigma_{u0}^2 + 2\sigma_{u01}Z_{ij} + \sigma_{u1}^2Z_{ij}^2}{3.29 + \sigma_{u0}^2 + 2\sigma_{u01}Z_{ij} + \sigma_{u1}^2Z_{ij}^2}$$

where σ_{u0}^2 and σ_{u1}^2 are the variances of intercept and slope at country-level and σ_{u01} is the random effect covariance.

4.3.3 Model Estimation and Modelling Strategy

The multilevel random slope model is estimated by using *iterative generalised least squares* (IGLS) method in the MLwiN software (Rasbash *et al.*, 2015). This is a common algorithm to obtain *full maximum likelihood* estimates for analysing hierarchical data with continuous outcome. The estimation is performed by MLwiN version 2.25 through R (R Core Team, 2016) using the package R2MLwiN (Zhang *et al.*, 2016).

Meanwhile, the multilevel random slope cumulative ordinal logit models for the ordinal outcomes are estimated by using Markov Chain Monte Carlo (MCMC) method in the MLwiN software (Browne, 2014). Non-informative priors are assumed. A burn-in length of 5,000 and iteration of 2,500,000, using the first order penalised (or predictive) quasi likelihood as starting values for the sampling (Goldstein, 2011). All the estimations are also performed by MLwiN version 2.25 through R (R Core Team, 2016) using the package R2MLwiN (Zhang *et al.*, 2016). In order to speed up the estimation process, we first run five models (burn-in length of 5,000 and iteration of 500,000) with the same model specification but with different starting values. These five models are then manually combined by joining the MCMC chains using the package coda (Plummer *et al.*, 2006) in R.

Despite using different estimation methods for continuous and ordered categorical outcomes, the modelling strategy is similar for both models. For the continuous outcome, model building begins with only one random term at the individual level while model construction starts with an empty model without any random term for the ordered categorical outcomes. A country level random effect is then added to the model and its significance is tested using a deviance test (for continuous outcome) and a Wald test and the 95% credible interval (for ordinal outcomes). In the case of the continuous outcome, as the estimation method is based on IGLS and variance components are not normally distributed, using a deviance test is preferable. Meanwhile, when modelling non-normal data (i.e., the ordinal outcomes) where MCMC estimation is used, the Wald test is preferred (Hox, Moerbeek and van de Schoot, 2018). We use one-sided *p*-value for the significance testing as variances cannot be negative (Snijders and Bosker, 2012). Since the Wald test and the 95% credible interval give similar results, only the Wald test is presented in the result section for the three ordinal outcomes. Meanwhile, the 95% credible interval is reported in Appendix C (Tables C.13, C.14, C.15 and C.16). After identifying the random structure, blocks of explanatory variables are included as fixed effects. We adopt a forward selection strategy for the selection of independent variables. Information on interview mode is added to the null model as control variable before the inclusion of other covariates. Afterwards, blocks of explanatory variables at the individuallevel (in the order of sociodemographics, personal values and environmental values) are

considered, followed by the inclusion of country-level variables (in the order of economic-and-education-development-, environment-, demographic- and political-related variables).

For model comparison, a likelihood ratio test is used for the multilevel random slope model (continuous outcome on the general environmental behaviour) while the deviance information criterion (DIC) is used for the multilevel random slope cumulative ordered logit model (ordinal outcomes on the home-, purchasing-, transport- and recycling-related environmental behaviours). Since the Wald test allows multiple parameters for a categorical variable to be tested simultaneously, we use it to test the significance of categorical variables in the fixed effects for both types of models (Snijders and Bosker, 2012). The Wald test is also used to test the significance of continuous variables in the fixed effects for both types of models. The degree of freedom for testing country-level variable is N-q-1, where N is the number of country and q is the number of country-level variables (Snijders and Bosker, 2012). The least significant variable with p-value larger than 0.05 is removed from the model. Models are then re-fitted until all variables in the same block are significant at the 5% level of significance. In the case where variables become insignificant when more blocks of variable are added, the insignificant variable is removed.

After the random intercept model is obtained for each outcome, we include a random slope on the variable of environmental attitude so that the effect of this variable on the outcome variable is allowed to vary across country. As one of the aims of this study is to investigate the relationship between environmental attitude and environmental behaviour, only environmental attitude is included as a random slope. It results in a random slope model with two extra parameters. The significance of these two random effect terms is then tested using a deviance test (for the continuous outcome) and a Wald test and the 95% credible interval (for the ordinal outcomes). Similar to the country-level random effect, a one-sided *p*-value is also used for the random slope because the variance cannot be negative. Meanwhile, a two-sided *p*-value is used to test the covariance between the random intercept and random slope. Again, as the Wald test and the 95% credible interval give similar results, only the Wald test results are presented and the 95% credible interval is reported in Appendix C (Tables C.13, C.14, C.15 and C.16). Finally, the insignificant variables are then added to the random slope models and their significances are tested again. If these variables become significant, they are included in the final model, otherwise, they are removed.

4.3.4 Model Validations and Diagnostics

After the final models for each of the outcomes are obtained, we perform relevant model diagnostic tests to ensure the assumptions of normality and homogeneity of variance are met. Normal plot and standardised residual plots are used to assess these two assumptions. As

shown in the residual plots (Figures C.8.1, C.9.1, C.10.1, C.11.1 and C.12.1) in the Appendix C, the residuals are approximately normally distributed. Furthermore, the assumption of homoscedasticity is also valid for all the models (see Figures C.9.2, C.10.2, C.11.2 and C.12.2 in the Appendix C).

In order to test the assumption of the proportional odds for multilevel cumulative ordered logit models for the four ordinal outcomes, we compare the final multilevel cumulative ordered logit models with a similar model that has the assumption partially relaxed. The DIC statistics for the relaxed models are 89,815.8, (home-related environmental behaviour), 87836.6 (purchasing-related environmental behaviour), 74,612.1 (recycling-related environmental behaviour) and 93,303.9 (transport-related environmental behaviour) respectively. Compared to the DIC statistics from the corresponding final models in Tables 4-11, 4-12, 4-13 and 4-14, the differences in DIC statistics between the relaxed and the corresponding final models are negligible. Therefore, the assumptions are valid.

Finally, we calculate the effective sample size and Raftery-Lewis diagnostic statistics to investigate whether the MCMC algorithms have converged during model estimations. Visual plots, including trace plot and kernel density plot for the posterior distribution are also included to assist this investigation. Results from these diagnostic tests also indicate that convergence is obtained for the four ordinal outcomes (see Figures C.9.3, C.10.3, C.11.3 and C.12.3, as well as Tables C.9.4, C.10.4, C.11.4 and C.12.4).

4.4 Results and Discussion

4.4.1 Exploration of Random Effects Specifications

This paper presents five multilevel models: one multilevel random slope model for a continuous outcome and four multilevel random slope cumulative ordinal logit models. Since multilevel models for continuous and ordinal outcomes use different estimation methods and they have different model specifications, we will first examine the random effect specifications for the model of general environmental behaviour (continuous outcome) and then we will look into the specifications for models of the four specific environmental behaviours (ordinal outcomes).

Model construction for the outcome of general environmental behaviour begins with a single-level model (Model 0.0). Afterwards, a country random effect is then included in the model (Model 0.1). Table 4-10 presents the estimated variances, the corresponding standard errors of different random effect terms and the deviance values for the four different models: Model 0.0 is an empty single-level model, Model 0.1 is an empty 2-level random intercept model,

Model 0.2 is a 2-level random intercept model which contains all significant fixed effect variables and Model 0.3 is the final random slope model with all significant fixed effect variables. A likelihood ratio test is conducted between Models 0.0 and 0.1. The results show that there are significant country differences and hence Model 0.1 is preferable to Model 0.0 (test for random intercept: $X^2(1) = 7,462.7, p < 0.001$). Based on Model 0.1, blocks of fixed effect explanatory variables are added into the model using a forward selection method. After obtaining the random intercept full model, a random slope is included on the variable environmental attitude. Result from the likelihood ratio test shows that there are differences between countries in the relationship between their people's environmental attitude (test for random slope: $X^2(2) = 271.2, p < 0.001$).

Meanwhile, model building for home-, purchasing-, recycling- and transport-related environmental behaviours starts with a single-level empty logit model which contains no random effect terms (Models 1.0, 2.0, 3.0 and 4.0). The estimated variances, corresponding standard errors and DIC statistics for the models on four different outcome variables are presented in Tables 4-11, 4-12, 4-13 and 4-14.

The inclusion of the country random effect (Models 1.1, 2.1, 3.1 and 4.1) reduces the DIC statistics of the corresponding empty models. These country random effect terms are all statistically significant at the 1% level, providing evidence that there are substantial country differences. The inclusion of significant fixed effects further decreases the DIC statistics for all outcomes (comparing Models 1.2, 2.2, 3.2 and 4.2 with the corresponding two-level empty models). Finally, we allow the effect of environmental attitude on behaviour to vary across countries by including a random slope on the variable environmental attitude. Again, the DIC statistics drop when the random slope is added to the models (comparing Models 1.3, 2.3, 3.3 and 4.3 with Models 1.2, 2.2, 3.2 and 4.2). The DIC diagnostics for these models suggest that the introduction of a random slope greatly improves the models.

There is hence sufficient evidence that the effect of individuals' environmental attitude on different types of environmental behaviours varies across countries. Therefore, a two-level random slope modelling approach is adopted on the general environmental behaviours and the four specific behaviours in this study.

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Table 4-10 Variances and Deviances of Multilevel Models on General Environmental Behaviour

	Mo	Model 0.0 (single-level)		del 0.1	Mo	del 0.2	Mo	del 0.3
	(sing			(empty random intercept)		(full random intercept)		ndom slope)
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)
Individual								
σ_e^2	16.0770	(0.1063)***	13.6057	(0.0900)***	11.1379	(0.0737)***	11.0543	(0.0731)***
Country								
σ_{u0}^2			2.0870	(0.5162)***	0.2680	(0.0678)***	0.2444	(0.0624)***
σ_{u01}							-0.0049	(0.0055)
σ_{u1}^2							0.0035	(0.0010)***
Deviance		256,982.7		249,520.0		240,300.8		240,029.6

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 4-11 Variances and DICs of Multilevel Models on Home-related Environmental Behaviour

	Mo	Model 1.0 (single-level)		Model 1.1 (empty random intercept)		Model 1.2 (full random intercept)		Model 1.3 (final random slope)	
	(sing								
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	
Country									
σ_{u0}^2			0.4268	(0.1152)***	0.2942	(0.0859)***	0.2876	(0.0823)***	
σ_{u01}							-0.0016	(0.0027)	
σ_{u1}^2							0.0006	(0.0002)**	
DIC		99,601.1		94,698.2		89,932.9		89,814.8	

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 4-12 Variances and DICs of Multilevel Models on Purchasing-related Environmental Behaviour

	Mo	del 2.0	Model 2.1		Model 2.2		Model 2.3 (random slope)	
	(sing	(single-level)		(empty random intercept)		om intercept)		
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)
Country								
σ_{u0}^2			0.3091	(0.0834)***	0.1844	(0.0565)***	0.1740	(0.0523)***
σ_{u01}							0.0035	(0.0031)
σ_{u1}^2							0.0012	(0.0004)***
DIC		98,432.8		94,435.3		88,142.4		87,838.2

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Table 4-13 Variances and DICs of Multilevel Models on Recycling-related Environmental Behaviour

		Model 3.0 (single-level)		Model 3.1 (empty random intercept)		Model 3.2 (full random intercept)		Model 3.3 (random slope)	
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	
Country									
σ_{u0}^2			1.6819	(0.4477)***	0.4625	(0.1368)***	0.4715	(0.1324)***	
σ_{u01}							0.0035	(0.0048)	
σ_{u1}^2							0.0012	(0.0003)***	
DIC		95,774.3		78,844.7		74,823.6		74,610.0	

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

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Table 4-14 Variances and DICs of Multilevel Models on Transport-related Environmental Behaviour

		Model 4.0 (single-level)		Model 4.1 (empty random intercept)		Model 4.2 (full random intercept)		del 4.3 om slope)
	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)	Variance	(S.E.)
Country								
σ_{u0}^2			0.1503	(0.0407)***	0.0707	(0.0239)**	0.0741	(0.0258)**
σ_{u01}							-0.0031	(0.0024)
σ_{u1}^2							0.0010	(0.0003)***
DIC		99,871.0		97,779.1		93,505.4		93,305.4

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

4.4.2 Discussion of the Final Models - Random Effects

In order to understand how individual and country influence individuals' environmental behaviours differ, this section discusses the changes in random variations by including both individual- and country-level variables. We will first examine the general environmental behaviours. Afterwards, the four specific environmental behaviours will be discussed.

4.4.2.1 General Environmental Behaviour

As presented in Table 4-10, the individual and country variances of the empty random intercept model (Model 0.1) of general environmental behaviour account for 86.7% and 13.3% of the total variation respectively. After controlling for the interview mode, the unexplained variations for individual- and country-levels become 91.3% and 8.7%. Table 4-15 shows the estimates of the individual and country random effects and the corresponding VPCs as blocks of explanatory variables are included to the empty random intercept model. As individual sociodemographic variables are added into the model (after controlling for the modes of interview), the individual level VPC reduces very slightly to 90.9%. The inclusion of other individual-level variables (personal values and environmental values) increases the total variation explained by within country-level by approximately 2.3%. When country-level variables enter the model, the VPC at the individual level further increases to 97.7%. This indicates that part of the individual differences can be explained by country-level variables. The VPC of country level increases to 9.1% after the inclusion of individual sociodemographic variable. It reduces to 8.3% and 7.0% after variables related to individual's personal values and environmental values are added to the model. As expected, there is a substantial reduction in the country random variance when the country-level variables are included in the model.

After obtaining the full random intercept model (Model 0.2 in Table 4-10), we allow the effect of individual's environmental attitude on behaviour to vary across countries by including a random slope on this individual-level variable. In order to obtain more interpretable estimates, this continuous variable is centred at its grand mean of 14.7. Model 0.3 in Table 4-10 presents the estimates of individual and country random effects for the final model. In the final model, the total variance explained by each level become a quadratic function of environmental attitude: $11.299 - 0.010Z_{ij} + 0.004Z_{ij}^2$. Figure 4-4 shows how the country-level VPC varies with individual's environmental attitude. The total variation explained by the country variance decreases as the environmental attitude increases to the global mean. Then, the VPC increases as the attitude increases.

The caterpillar plots for the ranked residuals with confidence intervals for both random intercept and random slope are shown in Figures 4-5 and 4-6. There are 33 residuals in each plot, one for each country. The width of the confidence interval associated with the corresponding country depends on the standard error of the respective country's residual estimate. In Figure 4-5, the residuals represent country departure from the overall mean of environmental behaviour score when all countries' environmental attitude score equal to the global environmental attitude average at 14.7. United States (US), Netherlands (NL), Latvia (LV) and Norway (NO) have lower-than average environmental behaviours while Argentina (AR), Mexico (MX) and Switzerland (CH) are countries with above-average environmental behaviour scores. Meanwhile, the residuals in Figure 4-6 demonstrate country departure from the average effect of environmental attitude on behaviour. The effect of environmental attitude in Mexico (MX), Philippines (PH), Republic of Korea (KR) and Japan (JP) are significantly lower from the average effect. Finally, Figure 4-7 illustrates predicted environmental behaviour obtained from the final random slope model. The black line presents the average effect of environmental attitude on behaviour while the grey lines represents 33 different countries from our data. As shown in the figure, most slopes are upwards but there are a few that are downwards. The downward slopes of Mexico (MX), Philippines (PH), Republic of Korea (KR) and Japan (JP) indicate there is a negative relationship between environmental attitudes and behaviours in these countries.

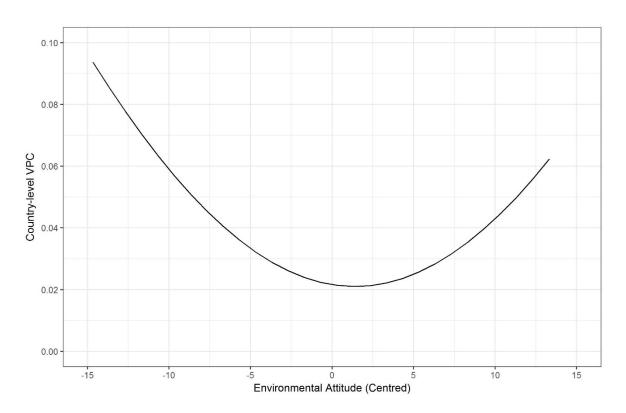


Figure 4-4 Country-level VPC for the Final Model of General Environmental Behaviour

Table 4-15 Estimates of the Individual and Country Random Effects Variances as Blocks of Explanatory Variables are added to the Multilevel Model: General Environmental Behaviour

		nates of the Indiv Idom Effect Vari			Estimates of the Country Random Effect Variance			
	Variance	(S.E.)	VPC	Variance	(S.E.)	VPC	Deviance	
None	13.6057	(0.0900)***	0.867	2.0870	(0.5162)***	0.133	249,520.0	
Added Survey Design (6)	13.6028	(0.0900)***	0.913	1.2913	(0.3219)***	0.087	249,494.5	
Added Individual's Sociodemographics (31)	13.1069	(0.0867)***	0.909	1.3169	(0.3266)***	0.091	247,796.9	
Added Individual's Personal Values (12)	12.8842	(0.0852)***	0.917	1.1689	(0.2888)***	0.083	247,009.2	
Added Individual's Environmental Values (6)	11.1380	(0.0737)***	0.930	0.8323	(0.2068)***	0.070	240,337.6	
Added Country-level Variables (5)	11.1379	(0.0737)***	0.977	0.2680	(0.0678)***	0.023	240,300.8	

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

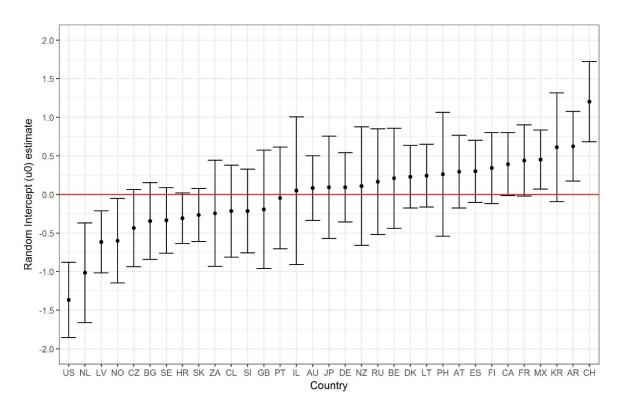


Figure 4-5 Country-level Random Intercept Residuals and 95% Confidence Interval for General Environmental Behaviour

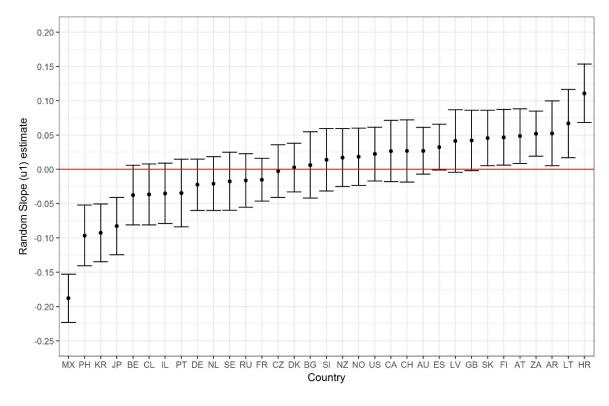


Figure 4-6 Country-level Random Slope Residuals and 95% Confidence Interval for General Environmental Behaviour

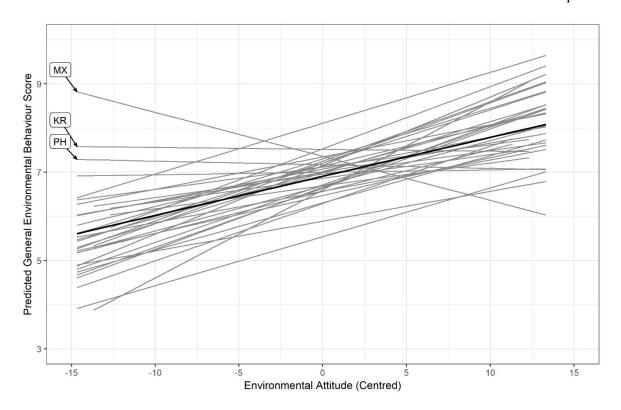


Figure 4-7 Predicted Country Lines from the Final Random Slope Model for General Environmental Behaviour

4.4.2.2 Specific Environmental Behaviours

After discussing the general environmental behaviour score, we will examine the four specific environmental behaviours (home-, purchasing-, recycling- and transport-related behaviours) in the following paragraphs. These behaviours are measured as ordinal outcomes. Therefore, these outcomes are modelled using a multilevel cumulative ordered logit modelling approach.

Home-related Environmental Behaviour

Country variance accounts for 11.5% of the total variation in explaining individuals' behaviour in the empty random intercept model (see Table 4-16). The VPC decreases to 10.6% after controlling for the mode of interview. When information about individuals' sociodemographics are included to the model, there is an increase in the country-level VPC. Nevertheless, further inclusion of individual personal and environmental values reduces the VPC by 10%. As one would expect, a substantial decrease of 17% in the country VPC is observed when country-level variables are added to the model.

After adding individuals' environmental attitude as a random slope to the full random intercept model, the country variance depends on environmental attitude. The estimated covariance between the intercept and slope is -0.0016 (see Model 1.3 in Table 4-11) and the correlation is -0.12. However, the estimated covariance is not significant at the 5% level. There is no significant correlation between overall home-related behaviour and the effect of

environmental attitude on these behaviours. As shown in Figure 4-20 on page 166, countrylevel VPC decreases gradually when there is greater concern about the environment. The caterpillar plots presented in Figures 4-8 and 4-9 illustrate the ranked residuals for the random intercept and slopes. At the global environmental average, Sweden (SE), Norway (NO), Bulgaria (BG) and Chile (CL) are significantly less environmentally friendly in homerelated behaviour, while Republic of Korea (KR), Spain(ES), Philippines (PH), Mexico (MX), France (FR) and Argentina (AR) are significantly greener (see Figure 4-8). Meanwhile, the effect of environmental attitude on home-related environmental behaviours in Mexico (MX), Republic of Korea (KR), Philippines (PH) and Japan (JP) are different from the overall average effect at the 5% level (see Figure 4-9). As discussed in the methodology section, the attitude effect is assumed to be proportional. Therefore, rather than presenting both the log-odds of being in the 'low participation' category (versus being above 'low participation') and being in the category of 'some participation' (versus being above 'some participation'), we present the predicted log-odds function (i.e. $\beta^T X_{ij} + u_{0j} + u_{1j} Z_{ij}$) in Figure 4-10. As shown in the figure, there are two country lines (Mexico (MX) and Republic of Korea (KR)) with negative slopes. This suggests that there is a negative relationship between home-related behaviours and attitude in these countries.

Table 4-16 Estimates of the Country Random Effect Variances as Blocks of Explanatory Variables are added to the Multilevel Model: Home-related Behaviour

	Variance	(S.E.)	VPC	DIC
None	0.4268	(0.1152)***	0.115	94,698.2
Added Survey Design (6)	0.3907	(0.1086)***	0.106	94,701.4
Added Individual's Sociodemographics (26)	0.4061	(0.1164)***	0.110	93,924.1
Added Individual's Personal Values (6)	0.4083	(0.1172)***	0.110	93,757.0
Added Individual's Environmental Values (7)	0.3595	(0.1028)***	0.099	89,933.1
Added Country-level Variable (1)	0.2942	(0.0859)***	0.082	89,932.9

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

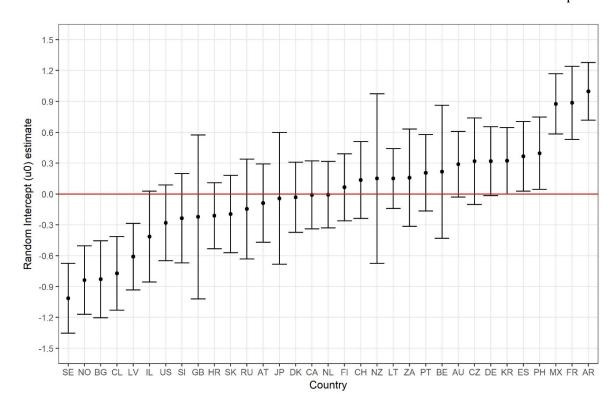


Figure 4-8 Country-level Random Intercept Residuals and 95% Confidence Interval for Home-related Environmental Behaviour

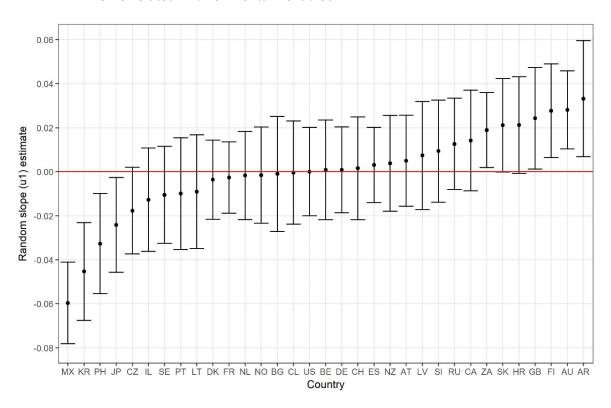


Figure 4-9 Country-level Random Slope Residuals and 95% Confidence Interval for Homerelated Environmental Behaviour

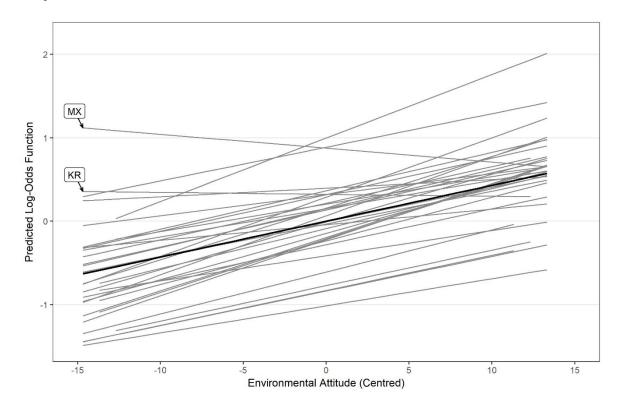


Figure 4-10 Predicted Log-Odds Function for Home-related Environmental Behaviour

Purchasing-related Environmental Behaviour

In the empty random intercept model, country variance accounts for 8.6% of the total variation in individuals' purchasing-related environmental behaviour (see Table 4-17). After controlling for the mode of interview, country-level VPC decreases to 8.1%. Overall, entering individual level variables to the model, the total variance explained by country-level reduces to around 7.0%. As expected, entering country-level variables further reduces the country-level VPC from 7.0% to 5.3%. There is more than a quarter of the individuals' variation within country that can be explained by national level factors.

Table 4-17 Estimates of the Country Random Effect Variances as Blocks of Explanatory Variables are added to the Multilevel Model: Purchasing-related Behaviour

	Variance	(S.E.)	VPC	DIC
None	0.3091	(0.0834)***	0.086	94,435.3
Added Survey Design (6)	0.2903	(0.0833)***	0.081	94,430.6
Added Individual's Sociodemographics (28)	0.3159	(0.0937)***	0.088	93,363.0
Added Individual's Personal Values (11)	0.2557	(0.0763)***	0.072	92822.3
Added Individual's Environmental Values (6)	0.2460	(0.0729)***	0.070	88,142.9
Added Country-level Variables (2)	0.1844	(0.0565)***	0.053	88,142.4

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

The country-level VPC of the final random slope model is shown in Figure 4-20 on page 166. The total variation explained by the country-level variance drops when concern in the environment increases. However, as environmental attitude further increases, the country-

level VPC no longer decreases but increases. The estimated covariance between the random intercept and slope is 0.0035 (see Table 4-12). As the covariance is not significant, no association between the overall purchasing-related behaviour and the effect of attitudes on the behaviour is observed. For purchasing-related behaviour, Portugal (PT), Norway (NO), Slovakia (SK), South Africa (ZA) and Netherlands (NL) are less environmentally friendly than the overall average (see Figure 4-11). Meanwhile, Republic of Korea (KR), Austria (AT), Lithuania (LT), Latvia (LV) and Switzerland (CH) are greener countries. The effect of environmental attitude on behaviour in Mexico (MX), Philippines (PH), Japan (JP), Republic of Korea (KR) and Netherlands (NL) is significantly different from the overall average. In particular, Mexico (MX) is the only country with a negative relationship which is shown in Figure 4-13.

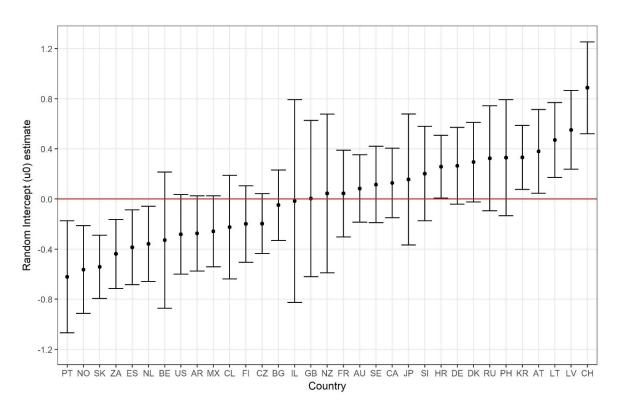


Figure 4-11 Country-level Random Intercept Residuals and 95% Confidence Interval for Purchasing-related Environmental Behaviour

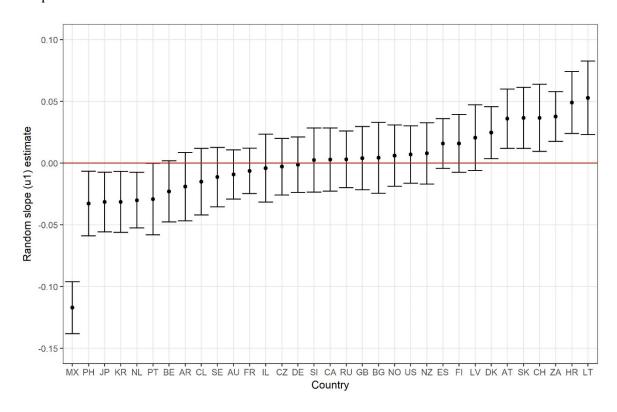


Figure 4-12 Country-level Random Slope Residuals and 95% Confidence Interval for Purchasing-related Environmental Behaviour

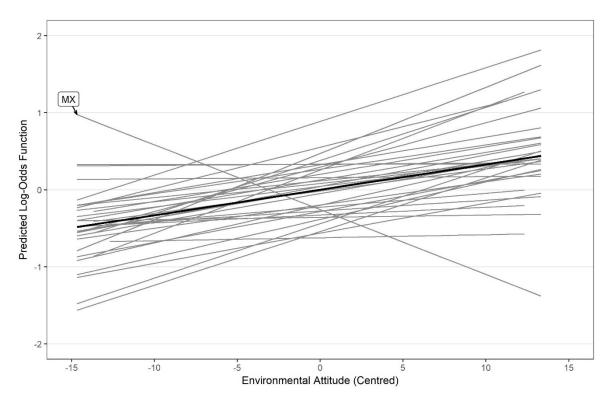


Figure 4-13 Predicted Log-Odds Function for Purchasing-related Environmental Behaviour

Recycling-related Environmental Behaviour

The country variance explains more than 33% of the total variation among individuals' recycling-related behaviours (Table 4-18). As mode of interview is controlled for, the country VPC drops substantially to 18.7%. The inclusion of sociodemographic information at individual level increases the country variance. However, it decreases by around 3% when further individual level information is added to the model. As expected, country-level variable reduces the VPC by 35%. This implies that country factors have an important role in explaining individuals' variation across nations.

Table 4-18 Estimates of the Country Random Effect Variances as Blocks of Explanatory Variables are added to the Multilevel Model: Recycling-related Behaviour

	Variance	(S.E.)	VPC	DIC
None	1.6819	(0.4477)***	0.338	78,844.7
Added Survey Design (6)	0.7562	(0.2079)***	0.187	78,832.9
Added Individual's Sociodemographics (17)	0.7909	(0.2223)***	0.194	76,988.3
Added Individual's Personal Values (5)	0.7927	(0.2243)***	0.194	76,702.3
Added Individual's Environmental Values (6)	0.7688	(0.2166)***	0.189	74,823.9
Added Country-level Variables (2)	0.4625	(0.1368)***	0.123	74,823.6

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

There is a quadratic relationship between environmental attitude and the proportion of variance explained by the country random effect (see Figure 4-20 on page 166). As the estimated covariance between the attitude and the recycling-related behaviour is not significant ($\sigma_{u01}=0.0035$), a country with an above-average engagement in recycling is no more or less likely to have an above-average attitude difference than a country with a below-average engagement in recycling. Across all 33 countries, Japan (JP), Denmark (DK), United States (US) and Croatia (HR) are less likely to recycle while Canada (CA), Australia (AU), Slovenia (SI), Belgium (BE), France (FR), Spain (ES) and Republic of Korea (KR) are significantly more likely to engage in recycling-related behaviour (Figure 4-14). In terms of the effect of attitude on recycling-related behaviour, Mexico (MX), Russian Federation (RU), Philippines (PH), Netherlands (NL), Japan (JP) and Denmark (DK) are significantly different from the overall effect (Figure 4-15). As shown in Figure 4-16, Mexico (MX), Russian Federation (RU) and Philippines (PH) have a negative relationship between attitude and behaviour.

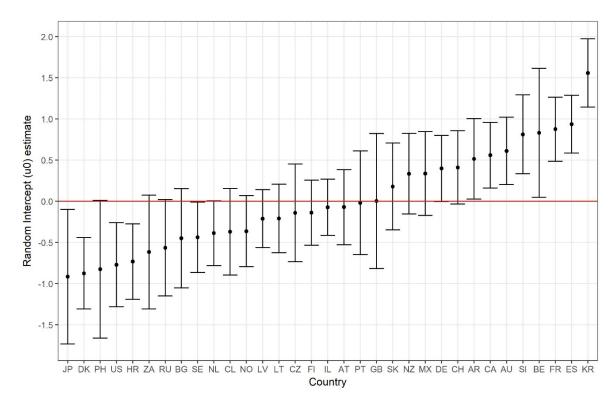


Figure 4-14 Country-level Random Intercept Residuals and 95% Confidence Interval for Recycling-related Environmental Behaviour

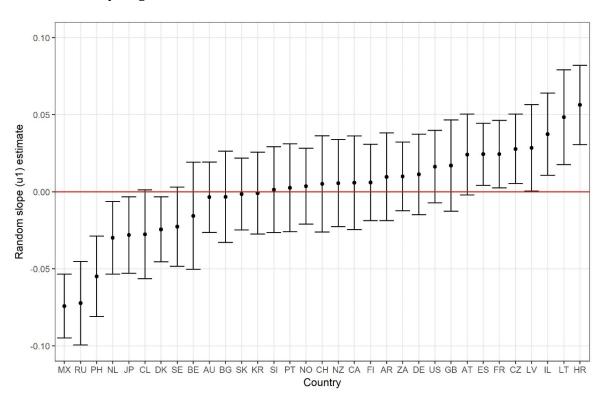


Figure 4-15 Country-level Random Slope Residuals and 95% Confidence Interval for Recycling-related Environmental Behaviour

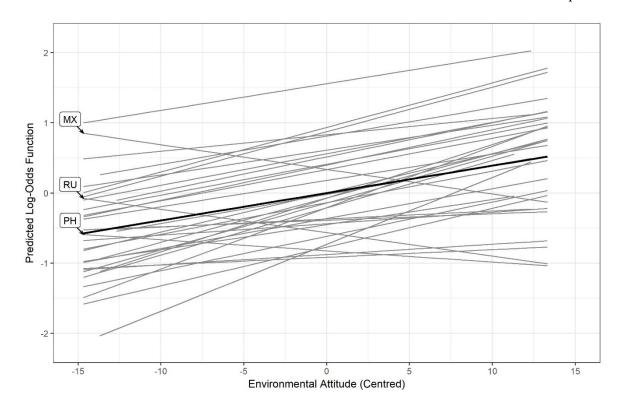


Figure 4-16 Predicted Log-Odds Function for Recycling-related Environmental Behaviour

Transport-related Environmental Behaviour

The total variation between individuals across countries explained by country variance is 4.4% for the empty random intercept model (Table 4-19). Country level VPC decreases slightly to 4.1% after controlling for the mode of interview. There is an increase of 23% in country variance when individual's sociodemographic variables are added into the model (from 0.1415 to 0.1736). As personal and environmental values are included, the country level VPC decreases from 5.0% to 3.8%. The inclusion of environmental values reduces the VPC more than the inclusion of personal values (22% compare with 2.0%). Unsurprisingly, when variables at country-level are included in the model, country variance decreases by approximately 45%

Table 4-19 Estimates of the Country Random Effect Variances as Blocks of Explanatory Variables are added to the Multilevel Model: Transport-related Behaviour

	Variance	(S.E.)	VPC	DIC
None	0.1503	(0.0407)***	0.044	97,779.1
Added Survey Design (6)	0.1415	(0.0407)***	0.041	97,780.7
Added Individual's Sociodemographics (33)	0.1736	(0.0512)***	0.050	96444.3
Added Individual's Personal Values (12)	0.1691	(0.0517)***	0.049	95811.7
Added Individual's Environmental Values (6)	0.1286	(0.0389)***	0.038	93,505.2
Added Country-level Variables (3)	0.0707	(0.0239)***	0.021	93,505.4

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

When individual's environmental attitude is included as a random slope in the full random intercept model, the VPC of country-level becomes a quadratic function of environmental attitude (Figure 4-20 on page 166). Again, the estimated covariance between the intercept and slope is insignificant at the 5% level ($\sigma_{u01} = -0.0031$). As shown in Figure 4-17, there are significantly lower participation in transport-related behaviour in South Africa, United States, Sweden and Netherlands. Meanwhile, people from Germany (DE), Latvia (LV), Argentina (AR), Austria (AT), Switzerland (CH), and Mexico (MX) are more likely to travel green in their daily lives. The effect of attitude on transport-related behaviour in Israel (IL), Mexico (MX), Chile (CL), Portugal (PT), Japan (JP) and Russian Federation (RU) are significantly different from the global average (Figure 4-18). Among these countries, Israel (IL), Mexico (MX), Chile (CL) and Portugal (PT) have a negative relationship between attitude and transport-related behaviour (Figure 4-19). Furthermore, there are almost no effects of attitude on behaviour in Japan (JP) and Russian Federation (RU).

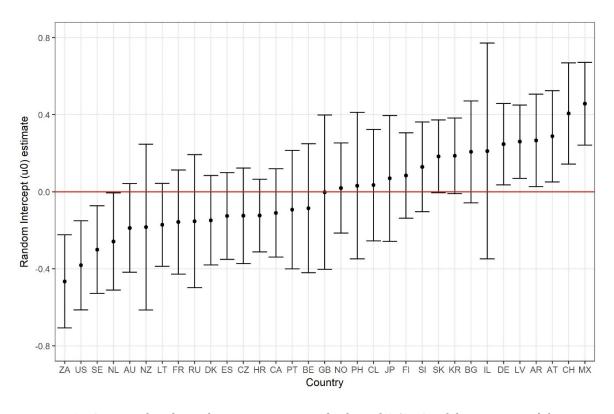


Figure 4-17 Country-level Random Intercept Residuals and 95% Confidence Interval for Transport-related Environmental Behaviour

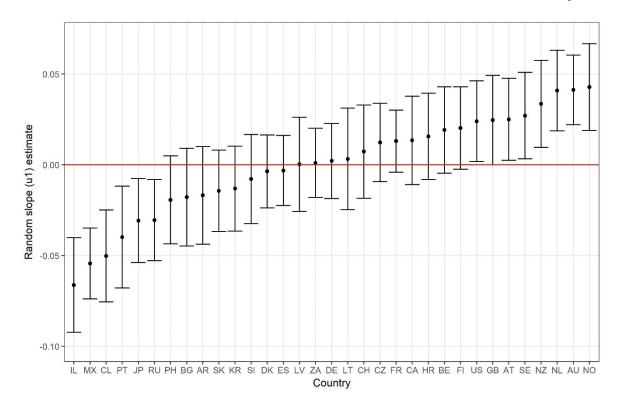


Figure 4-18 Country-level Random Slope Residuals and 95% Confidence Interval for Transport-related Environmental Behaviour

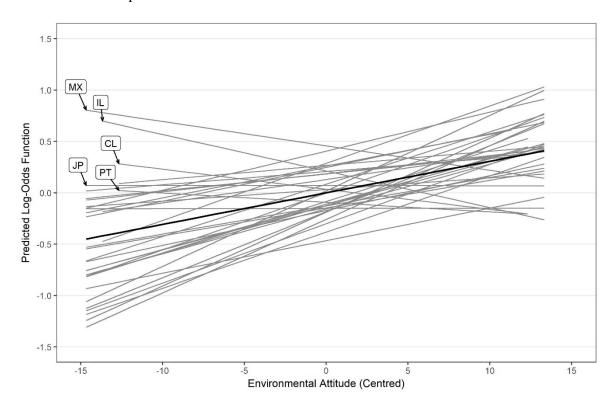


Figure 4-19 Predicted Log-Odds Function for Transport-related Environmental Behaviour

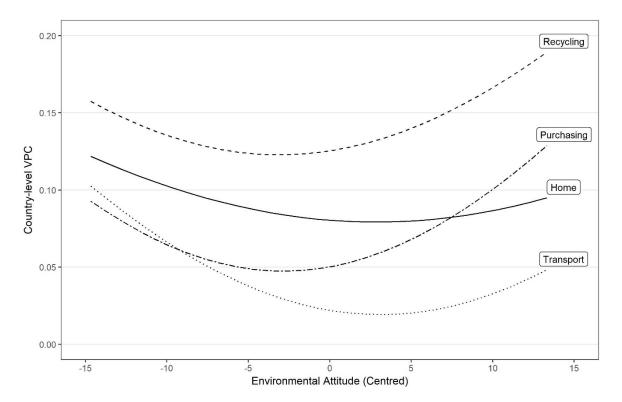


Figure 4-20 Country-level VPC for the Final Model of Home-, Purchasing-, Recycling- and Transport-related Environmental Behaviour`

4.4.3 Discussion of the Final Models - Fixed Effects

The fixed effects of the final random slope models for all outcomes (in the following order: general environmental behaviour, home-, purchasing-, recycling- and transport-related behaviours) are shown in Table 4-20 on page 170. For the continuous outcome on general behaviour, the estimated coefficients and corresponding standard errors are presented. Meanwhile, we report the odds ratios and corresponding standard errors for the remaining four ordinal outcomes on home-, purchasing-, recycling- and transport-related behaviours.

In general, women are more likely to behave environmentally friendly than men. This is particularly true for home-, purchasing- and transport-related behaviours. Among these three types of behaviours, the odds for female are 22.7%, 30.0% and 27.0 % higher than the odds for male, holding the other fixed-effects in the respective model constant. These findings are consistent with the literature that studies gender differences (Zelezny, Chua and Aldrich, 2000; Hunter, Hatch and Johnson, 2004; Scannell and Gifford, 2013). However, the odds for female are 12.5% lower than the odds for male for recycling-related behaviours. Compared with the younger age group (aged between 15 and 30), those who are older (aged 31-45, 46-60, 61-75 and 76 or above) engage more often in green behaviours. This result is consistent across all types of behaviours being investigated. Similar results are also reported by Pinto *et al.* (2011) and Swami *et al.* (2011) who examine the age effect on environmental behaviours. Generally speaking, employment status has a significant effect in explaining individuals'

environmental behaviours, especially in recycling- and transport-related behaviour. Results show that employed individuals are less likely to behave green than those who are students, unemployed and homemakers. Education level is another important individual factor. Across four types of behaviours, those who are more educated tend to participate more in proenvironmental behaviours. According to Kollmuss and Agyeman (2002), when people are more educated, they are more knowledgeable about environmental problems and solutions to these problems. Therefore, our findings show a consistent result with the previous literature. Currently not married persons are less likely to engage in purchasing-related behaviours. Their odds are 8.6% lower than the odds for the currently married persons, holding the other fixed-effects in the model constant. However, they are more likely to recycle household waste and travel green than those that are married. Those who have never married also tend to recycle and travel in a more environmentally friendly way than those who are married. Nevertheless, the odds for married couples or partners to behave green in home- and purchasing-related behaviours are higher than those who have never married. Social status is insignificant in explaining behaviours related to recycling. However, it is highly significant in explaining the remaining three behaviours. Interestingly, those who ranked themselves as the bottom 10% of the society are more pro-environmental than those who consider themselves rich. This result is also applicable to home-, purchasing- and transport-related behaviours. These results contradict existing studies that middle- to uppermiddle-class people are more environmentally friendly behaved than the lower class people (Gifford and Nilsson, 2014). However, it provides some evidence to support the findings from Fairbrother (2012) that the poorer are more likely to behave green than those who are wealthy. Another significant individual-level factor is household size. Although it is not significant in explaining recycling-related behaviours, it remains significant in home-, purchasing- and transport-related behaviours. Individuals who live with others are found to be less likely to behave green. Similar findings are also reported in the literature (Büchs and Schnepf, 2013; Longhi, 2013). There is a weak relationship between area of residency and environmental behaviours. Those who live in small cities and rural areas are more likely to purchase green. However, they are, as one might expect given the greater distance, less likely to travel green than those who live in big cities. Public transport is more common in big cities; therefore, those who live in big cities are able to use more efficient public transport network.

Religion is only significant in explaining home-related behaviours. The odds for those who belong to a religion are 7.3% less than those who have no religion, holding the other fixed-effects in the model constant. We use voting history in the last general election to measure interest in politics and society. We assume those who voted in their last general election are more likely to be interested in politics and concerned about their society. Consistent results are observed across all types of behaviours. Those who voted in the last general election tend

to behave greener than those who did not. Our results on the influences of party affiliation and left-right ideology on environmental behaviours support the findings in existing literature (Feinberg and Willer, 2013; McCright and Dunlap, 2013; McCright, Xiao and Dunlap, 2014). In general, people with liberal views are more likely to behave environmental unfriendly than those who support the left ideology. As the views of people move from left to right, the tendency for them to engage in environmentally behaviours also decreases. This is particularly true for purchasing- and transport-related behaviours. In terms of left-right ideology, those who agree with private enterprise is the best way to solve economic problems are more likely to behave green in home-, purchasing- and recycling behaviours. On the other hand, people who believe their government should be responsible for reducing income differences tend to engage in all types of environmental behaviours. Post-materialistic value is another personal value that is important in explaining environmental behaviours, especially for behaviours related to purchasing and transport. People who are more materialistic are less likely to behave green than those who are post-materialistic. Again, these results are also consistent with existing studies that examine the relationship between post-materialism and environmental behaviours (Inglehart, 1995; Kilbourne and Pickett, 2008). In terms of social and political trusts, our results show that those who think most people can be trusted are greener than their counterparts. This is particularly true for purchasing- and transport-related behaviours. However, in contrast to the literature that there is a positive relationship between political trust and people's support on environmental protection, our results demonstrate that people who do not trust their own government engage in more home- and transport-related behaviours. Since the majority of the existing studies on political trusts focus on public support for government environmental protection policy, the effect of political trust may not be applicable for more personal daily behaviours. Unlike government's policy that require people's trust and support, daily behaviours are more personal and hence government's role become less important. Moreover, another possible reason is that people behave greener is a result of their doubtfulness in their government's action to improve the environment.

As one could expect, environmental values are found to be very significant in explaining all types of green behaviours. The higher the people perceived environmental risk, the more likely they behave environmentally friendly. According to the NAM and VBN, people's behaviour is initiated by problem awareness. As they are more aware of the environmental problems and the potential consequences, they behave in a way that they can reduce harms on the environments. As the NAM and VBN also suggest that people need to acknowledge the correct methods to address the problems that they are aware of, it is unsurprisingly that those who have more knowledge about the environment are more likely to behave green. Meanwhile, people who are more willing to make personal sacrifices for the environment and

are more concerned about environmental issues tend to engage more in pro-environmental behaviours. These results are consistent for four types of behaviours. This can be explained by the TPB that environmental attitudes and intentions are important in explaining people's environmental behaviours. Results show that individuals who perceived positive attitudes towards modern technology and sciences engage less in home-, purchasing- and transport-related behaviours. In other words, those who have negative views on modern technology are greener in these three behaviours. It is possible that they think modern technology may not be sufficient in solving environmental problems and hence they decide to act green to solve such problems. As expected, individuals who are more supportive of environmental justice are more environmentally friendly. Those who agree there should be international agreement for all countries to follow tend to behave green at home, purchase green and recycle wastes. Similarly, those who think that poorer countries should be expected to make less effort than richer countries also engage more often in both home- and recycling-related behaviours.

The Human Development Index (HDI) is a highly significant country-level variable that can be used to explain individual's general environmental behaviours. For a one-unit increase in the HDI, we expect to see about 9.8 units increase in the general environmental behaviour score. However, when we examine the four individual behaviours separately, this country-level effect diminishes. Another national level factor which is only significant in general behaviours but insignificant in the other four behaviours is population density. The denser the country, the more likely for people living there to act green in their daily lives. Results also show that satisfaction towards government's action on environmental problems is another important factor. This is particularly true for both recycling- and transport-related behaviours. People from countries with high level of satisfaction towards government actions are more likely to behave green. The Gini coefficient is a measure of inequality which ranges between zero and one. Zero indicates perfect equality while one indicates high inequality. Our results show when the Gini coefficient is high, people are less likely to recycle. In other words, in countries with high inequality, their people tend to recycle wastes less often than those who are from a country with more equal income. However, the Gini coefficient is insignificant in the other three behaviours. Finally, country's average trust in government and the Corruption Perception Index (CPI) are found to have a negative relationship with environmental behaviours. For purchasing-related behaviour, people from countries with low level of trust on their government are more likely to behave green. Also, individuals from more corrupt countries are more likely to purchase and travel green.

Table 4-20 Estimated Coefficients and Odds Ratios (ORs) for the Final Random Slope Multilevel Models

Variable	Category	G	eneral	1	lome	Pur	chasing	Re	cycling	Tra	ansport
(Reference Category)		β	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)
Multilevel Random Slope Model	Intercept	6.906	(0.254)***	-	-	-	-	-	-	-	-
Multilevel Random Slope Cumulative	Intercept 1	-	-	2.529	(0.072)***	1.277	(0.142)	0.875	(0.218)	1.557	(0.089)**
Ordered Logit Model	Intercept 2	-	-	0.343	(0.532)***	0.139	(1.310)***	0.224	(0.851)***	0.312	(0.444)***
			<u>Individu</u>	al Sociod	emographics \	<u>Variables</u>					
Gender (Male)	Female	0.616	(0.033)***	1.227	(0.015)***	1.300	(0.015)***	0.875	(0.017)***	1.270	(0.015)***
Age (15-30)	31-45	0.398	(0.056)***	1.146	(0.027)***	1.179	(0.027)***	0.224	(0.027)***	1.126	(0.029)***
	46-60	0.730	(0.059)***	1.329	(0.025)***	1.294	(0.026)***	2.802	(0.023)***	1.326	(0.026)***
	61-75	1.077	(0.077)***	1.656	(0.023)***	1.469	(0.026)***	5.084	(0.025)***	1.543	(0.029)***
	76+	1.337	(0.099)***	1.782	(0.028)***	1.531	(0.033)***	2.104	(0.031)***	1.865	(0.031)***
Employment status	Unemployed	0.254	(0.066)***					2.382	(0.044)	1.339	(0.029)***
(employed)	Student	-0.005	(0.080)					2.094	(0.058)**	1.419	(0.033)***
	Retired	0.343	(0.061)***					5.352	(0.031)***	1.325	(0.026)***
	Homemaker	0.163	(0.066)*					1.305	(0.038)*	1.161	(0.033)***
	Other	0.311	(0.074)***					1.280	(0.049)	1.284	(0.034)***

Variable	Category	G	eneral	I	lome	Pur	chasing	Re	cycling	Tra	ansport
(Reference Category)		β	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)
Highest education	Lowest qualification	0.392	(0.078)***	1.195	(0.038)***	1.108	(0.042)*	1.648	(0.036)***	0.950	(0.048)
(no formal qualification)	Intermediate secondary completed	0.261	(0.075)***	1.131	(0.039)**	1.099	(0.041)*	1.914	(0.036)***	0.885	(0.049)**
	Higher secondary completed	0.264	(0.075)***	1.113	(0.039)*	1.160	(0.038)***	2.014	(0.033)***	0.808	(0.054)***
	University degree uncompleted	0.210	(0.081)**	1.061	(0.045)	1.183	(0.041)***	0.957	(0.038)***	0.793	(0.059)***
	University degree completed	0.289	(0.081)***	1.022	(0.046)	1.231	(0.039)***	0.862	(0.035)***	0.847	(0.056)***
Marital status (currently married)	Currently not married	0.005	(0.048)	1.042	(0.026)	0.914	(0.030)**	1.289	(0.031)***	1.129	(0.024)***
	Never married	-0.201	(0.051)***	0.923	(0.031)**	0.828	(0.035)***	1.101	(0.040)***	1.141	(0.026)***
Self-rated social	20%	-0.420	(0.118)***	0.792	(0.090)**	0.821	(0.087)**			1.014	(0.069)
status (bottom 10%	30%	-0.453	(0.106)***	0.760	(0.085)***	0.861	(0.075)*			0.882	(0.072)*
in the society)	40%	-0.576	(0.104)***	0.711	(0.089)***	0.892	(0.071).			0.828	(0.075)**
	50%	-0.550	(0.101)***	0.732	(0.084)***	0.894	(0.069)			0.746	(0.081)***
	60%	-0.634	(0.104)***	0.649	(0.097)***	0.910	(0.069)			0.728	(0.085)***
	70%	-0.675	(0.108)***	0.658	(0.099)***	0.917	(0.071)			0.701	(0.092)***
	80%	-0.722	(0.116)***	0.634	(0.110)***	0.856	(0.081)*			0.686	(0.100)***
	90%	-0.569	(0.160)***	0.627	(0.152)***	1.027	(0.094)			0.705	(0.133)***
	100%	-0.269	(0.175)	0.713	(0.146)**	1.159	(0.091)			0.898	(0.116)
	(questions not asked)	-1.421	(0.447)**	0.361	1.145)*	0.812	(0.426)			0.543	(0.415)**

Variable	Category	Ge	eneral	l	Home	Pur	chasing	Re	cycling	Tra	ansport
(Reference Category)		β	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)
Household size	2-person household	0.000	(0.054)	1.024	(0.031)	1.035	(0.031)			0.848	(0.037)***
(1-person	3-person household	-0.158	(0.061)**	0.918	(0.039)*	0.953	(0.037)			0.800	(0.044)***
household)	4-person household	-0.169	(0.064)**	0.934	(0.040)	0.944	(0.039)			0.811	(0.045)***
	5+ person household	-0.056	(0.068)	0.993	(0.039)	0.956	(0.042)			0.905	(0.043)*
Region (Big city)	Small City					1.049	(0.023)*			0.940	(0.025)**
	Rural Area					1.166	(0.022)***			0.832	(0.030)***
			<u>Indivi</u>	dual Pers	onal Value Va	<u>riables</u>					
Belong to a Religion <i>(Yes)</i>	No			1.073	(0.022)**						
Voted in last GE	No	-0.345	(0.044)***	0.895	(0.027)***	0.872	(0.029)***	0.794	(0.034)***	0.905	(0.028)***
(Yes)	Not eligible to vote	-0.242	(0.083)**	0.861	(0.054)**	0.854	(0.056)***	0.824	(0.064)***	1.181	(0.040)***
Party affiliation	Centre, liberal	-0.132	(0.054)*			0.963	(0.033)			0.865	(0.035)***
(Far left, left, centre left)	Conservative, right, far right	-0.145	(0.048)**			0.929	(0.030)**			0.842	(0.032)***
	Other	0.285	(0.112)*			1.226	(0.053)**			1.218	(0.052)**
	No party affiliation	-0.027	(0.051)			0.994	(0.030)			0.935	(0.031)*
	(questions not asked)	-2.809	(0.570)***			0.290	(1.522)**			0.334	(0.996)***
Left-right ideology	Private enterprise	0.085	(0.015)***	1.049	(0.008)***	1.034	(0.008)***	1.050	(0.009)***		
	Income redistribution	-0.125	(0.015)***	0.954	(0.009)***	0.949	(0.009)***	0.976	(0.010)*	0.923	(0.009)***
Post-materialistic values (post-materialistic)	Neither post- materialistic nor materialistic	-0.151	(0.052)**			0.869	(0.035)***			0.934	(0.032)*
	Materialistic	-0.214	(0.058)***			0.798	(0.042)***			0.932	(0.035)*

Variable	Category	G	eneral	1	lome	Pur	chasing	Re	cycling	Tra	ansport
(Reference Category)	β	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)
Social and political	People are trustable	0.016	(0.008)*					1.029	(0.005)***	1.013	(0.005)**
trust	Government are trustable			0.984	(0.006)**					1.031	(0.005)***
			<u>Individu</u> :	al Enviror	ımental Value	Variables	<u>.</u>				
Environmental values	Environmental risk perception	0.116	(0.004)***	1.049	(0.002)***	1.067	(0.002)***	1.028	(0.002)***	1.029	(0.002)***
	Environmental knowledge	0.293	(0.009)***	1.134	(0.005)***	1.156	(0.005)***	1.098	(0.005)***	1.081	(0.005)***
	Willingness to make personal sacrifice	0.199	(0.006)***	1.080	(0.003)***	1.109	(0.003)***	1.051	(0.003)***	1.084	(0.003)***
	Environmental attitudes	0.088	(0.011)***	1.044	(0.005)***	1.034	(0.006)***	1.040	(0.006)***	1.031	(0.006)***
	Attitudes towards modern technology	-0.085	(0.006)***	0.952	(0.004)***	0.964	(0.004)***			0.949	(0.004)***
	International agreement	-0.192	(0.020)***	0.925	(0.013)***	0.948	(0.013)***	0.840	(0.015)***		
	Poor countries are expected less			1.019	(0.008)*			1.024	(0.009)**	0.988	(0.008)

Variable	Category	G	eneral	l	Home	Pur	chasing	Re	cycling	Tra	ansport
(Reference Category))	β	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)	OR	(S.E.)
				Country-	level Variable	<u>S</u>					
Country-level	Gini coefficient							0.947	(0.017)***		
	Corruption perception index	-0.319	(0.104)**			0.857	(0.076)*			0.915	(0.043)*
	Human development index	9.797	(2.324)***								
	% of pop satisfied with government's action	0.048	(0.009)***					1.030	(0.009)**	1.019	(0.005)***
	% of water quality			1.026	(0.010)*						
	% of air quality									0.969	(0.010)**
	Population density	0.002	(0.001)*								
	Average trust on government	-0.797	(0.188)***			0.739	(0.186)*				
				Survey Do	esign Variable	<u>S</u>					
Mode of interview	F2F interview (CAPI)	1.262	(0.366)***	0.861	(0.348)	2.666	(0.107)***	2.802	(0.116)**	1.868	(0.103)**
(F2F interview -	SC (interviewer)	1.844	(0.446)***	2.103	(0.184)	3.190	(0.111)**	5.084	(0.089)***	2.338	(0.090)***
PAPI)	SC (mailed)	1.859	(0.395)***	1.091	(0.259)	3.584	(0.084)***	2.104	(0.151)*	2.364	(0.085)***
	SC (CASI)	1.537	(0.386)***	0.990	(0.294)	3.106	(0.095)***	2.382	(0.134)**	2.153	(0.094)***
	SC (web)	1.682	(0.422)***	1.005	(0.294)	3.112	(0.101)***	2.094	(0.157)*	2.109	(0.103)***
	Phone interview	1.818	(0.463)***	0.989	(0.346)	3.050	(0.108)***	5.352	(0.069)***	2.129	(0.118)**

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05 grey area indicates covariate is not included in the respective final models

4.5 Exploration of the Impact of Mode of Interview on Countrylevel Variances

In the ISSP, there are six different types of interview modes: face-to-face interview (PAPI), face-to-face interview (CAPI), self-completed questionnaire (interviewer-administrated), selfcompleted questionnaire (mailed), self-completed questionnaire (CASI), self-completed questionnaire (web) and phone interview. As shown in the Table C.5 in Appendix C, 28 countries use only one interview mode and five countries use two interview modes to conduct the ISSP. To investigate the effect of interview mode on country-level variances, a two-level random intercept model and a two-level random slope model are fitted to all outcomes separately where the five dummy variables for mode of interview are removed. Then, the country-level random effects specifications of the new models without the dummies on interview mode are compared with corresponding final models (see Table 4-21 for the random intercept models and Table 4-22 for the random slope models). For the random intercept models, when the variables on mode of interview are removed from the models, there are substantial increases in the VPCs and country-level variances. The increment for the country-level variance ranges from 8.0% (home-related environmental behaviour) to 65.6% (general environmental behaviour). Similar results are also obtained for the random slope models. A sizable increase in the country-level variances can also be observed in the random slope models. These figures indicate that a large proportion of the unexplained variations for country-levels can be explained by how the interviews are conducted. Therefore, it is essential to control for the mode of interview in the models even though the effects may not be of substantial interest in this study.

Furthermore, some may argue that the interview mode should be treated as a random effect rather than a fixed effect. However, here, the modes of interview are regarded as unique categories rather than a sample of interview modes from a wider 'population' of interview mode. According to Snijders and Bosker (2012), the data contain barely sufficient information about the 'wider' population if there are less than ten categories. Therefore, it is problematic to view these six interview modes as a sample from a wider 'population'.

Moreover, we are not interested in the wider 'population' of interview mode but we would like to control for the possible impacts of interview modes on country-level variances. This study aims to identify how different individual- and country-level factors influence individuals' environmental behaviours and hence it is more appropriate to control as much as possible for the between-country variances than incorporating the mode of interview as an extra random effect. As a result, the mode of interview is treated as a fixed effect in our analyses (Goldstein, 2011; Snijders and Bosker, 2012).

Table 4-21 Summary of Country-level Variances and VPCs for the Final Random Intercept Model with and without Mode of Interview

	Random Intere Model with Model Interview	-	Random Intero Model without M Interview			
	Variance (S.E.)	VPC	Variance (S.E.)	VPC	Increase in VPC	Increase in Variance
General	0.2680 (0.0678)	0.024	0.4438 (0.1114)	0.038	63.0%	65.6%
Home	0.2942 (0.0859)	0.082	0.3176 (0.0889)	0.088	7.2%	8.0%
Purchasing	0.1844 (0.0565)	0.053	0.2546 (0.0739)	0.072	35.2%	38.1%
Recycling	0.4625 (0.1368)	0.123	0.6313 (0.1784)	0.161	30.6%	36.5%
Transport	0.0707 (0.0239)	0.021	0.1048 (0.0317)	0.031	47.1%	48.2%

Table 4-22 Summary of Country-level Variances for the Final Random Slope Model with and without Mode of Interview

	Random Slope M with Mode of Inte		Random Slope M without Mode Interview			
	Variance (S.E.)	VPC	Variance (S.E.)	VPC	Increase in VPC	Increase in Variance
General	0.2444 (0.0624)	-	0.4233 (0.1064)	-	-	73.2%
Home	0.2876 (0.0823)	-	0.3136 (0.0859)	-	-	9.0%
Purchasing	0.1740 (0.0523)	-	0.2423 (0.0694)	-	-	39.3%
Recycling	0.4715 (0.1324)	-	0.6557 (0.1792)	-	-	39.1%
Transport	0.0741 (0.0258)	-	0.1067 (0.0329)	-	-	44.0%

4.6 Conclusion

This paper examines the cross-country differences on individual's environmental behaviours and investigates how the relationship between individual's environmental attitudes on behaviour varies across countries using data from the ISSP 2010 Environmental module. It analyses the overall environmental behaviour, as well as four distinct behaviours which are related to home, purchasing, recycling and transport. The adoption of multilevel modelling successfully identifies the role of countries in explaining how people from these countries behave differently. Furthermore, to allow the relationship between attitude and behaviour to vary across countries, a random slope is included.

The random specifications in the final models explain how individual's environmental behaviours can be influenced by country differences. Regardless of the behaviours being studied, the country-level random effect is significant in explaining all behaviours. For the overall environmental behaviour, the country-level random effect contributes to 2.3% of the total variation among individuals after controlling for the fixed effects in the model. Furthermore, the country-level random effect also explains 2.1%, 5.3%, 8.2% and 12.3% of

the total individual's variation for transport-, purchasing-, home- and recycling-related behaviours respectively. Among these four specific behaviours, country differences play the largest role in explaining individuals' recycling-related behaviours. Policies for recycling differ across countries. Some countries have laws and regulations about recycling, while recycling may not be common in some other countries. For instance, it is easy to get access to recycling facilities in Germany and people can get money back when they recycle plastic and glass bottles. This encourage their people to recycle used plastics and glasses. In fact, the overall recycling rate in Germany reaches almost 50% and it is ranked third highest in the world (Waste Atlas Partnership, 2017). Meanwhile, according to Schwanse (2011), recycling in Mexico mainly depends on private enterprises and the Mexican government does not have much involvement in public policy on recycling. Therefore, it is not surprising that Mexico has a very low overall recycling rate of 3.3% (Waste Atlas Partnership, 2017). This illustrates why individual's recycling-related behaviours is highly contributed by the country-level random effect. For all behaviours, both individual- and country-level variables reduce the country variances. As expected, whilst the inclusion of individual-level variables reduces the country-level VPC, a greater reduction is achieved by including country-level variables.

The relationship between individual's environmental attitudes and behaviours is another focus of this paper. In order to examine such a relationship, we extend the random part of the hierarchical linear model by allowing the relationship between the outcome (i.e., individual's environmental behaviour) and environmental attitude to vary across countries. The inclusion of the random slope on all outcomes substantially reduces the DIC, indicating that the random slope model has a better fit than the corresponding random intercept model. In all final models, the random slope terms are statistically significant at the 1% level. However, the covariance between the random intercept and random slope is not significant across all outcomes. As the average environmental attitude increases, the individual's variation being explained by the country-level random effect decreases gradually and then increases again (see Figure 4-4 for the general environmental behaviour and Figure 4-20 for the four specific behaviours).

Based on the established theoretical frameworks and the literature on environmental behaviours, a set of individual- and country-level explanatory variables are selected to be included in the final model in order to understand the underlying determinants of individual's environmental behaviours. Most of the results are consistent with these theories and previous findings. After controlling for the mode of interview, a wide range of individual-level variables are found to be significant in influencing all four types of behaviours. These variables included gender, age, education level, marital status, interest in society and politics, left-right ideology, awareness of environmental problems, knowledge on environmental

issues, willingness to make personal sacrifice and environmental attitudes. A number of factors were found to be significant in only one or some of the separate environmental behaviours. In particular, the factors that are found to be significant in explaining the recycling-related behaviour are relatively different from the other three types of behaviours. Unlike the home-, purchasing- and transport-related behaviours, social status and household size are insignificant in understanding the recycling-related behaviour. As discussed, the country-level variance effect accounts for a large proportion of the random variances in explaining why people recycle. Therefore, it is unsurprising that the explanatory powers of individual-level covariates on recycling are not as powerful as in the case for the other three behaviours.

As argued by Steg and Vlek (2009), different types of environmental behaviours are not necessarily correlated. Behaviours can be motivated by different individual- and countrylevel factors. This paper confirms their argument as our results show that recycling-, home-, purchasing- and transport-related behaviours are subjected to influences from a variety of factors. Studying only the general environmental behaviour can lead to bias because generalising different types of behaviours may hide certain underlying trends and some effects may be cancelling out. Therefore, in addition to the substantive contribution, our findings also provide insights on how to examine environmental behaviours. The results provide evidence that analysing generalised environmental behaviour cannot provide a full picture in understanding environmental behaviours. For policy makers, it is important to understand the underlying factors for specific environmental behaviours so that proper interventions or policies can be implemented. Meanwhile, this paper also demonstrates the use of multilevel cumulative ordered logit models to analyse ordinal outcomes. Up to date, the majority of studies that investigated the country effect on specific environmental behaviours analyse the country-level information as fixed effects (Hunter, Hatch and Johnson, 2004; Duroy, 2008). Among studies that adopt a multilevel modelling approach, they always analyse generalised environmental behaviour in which the outcome is a continuous variable (Pisano and Lubell, 2017). When we measure specific environmental behaviour, the outcome is usually either dichotomous or ordinal. Treating dichotomous or ordinal data as continuous data in the analysis can lead to a downward bias (Hox, 2010). Therefore, it is important for the researchers to adopt the appropriate method when analysing specific environmental behaviours.

Chapter 5: Conclusion

This study investigates the underlying factors of individual's pro-environmental behaviours and examines the relationship between environmental attitudes and behaviours. Papers 1, 2 and 3 analyse general environmental behaviours and different types of environmental behaviours using a multilevel modelling approach. To examine the roles of household and interviewers on individual's reported environmental behaviours in the UK, Paper 1 uses a dataset form the Wave 4 of the Understanding Society, UK Household Longitudinal Study. To investigate household-level influences and to account for the cross-classified structure of interviewers and primary sampling units, cross-classified multilevel models are applied. Paper 2 extends the analysis from Paper 1 to investigate the household effect on three distinct environmental behaviours: home-, purchasing- and transport-related behaviours. It uses the same data as for Paper 1. Since these outcomes are ordinal variables, this paper applies a multilevel cross-classified cumulative ordered logit model. Paper 3 investigate cross-national comparison of general environmental behaviour and four specific environmental behaviours: home-, purchasing-, recycling- and transport-related environmental behaviours. This paper uses data from the International Social Survey Programme: 2010 Environmental III module. It also demonstrates the use of multilevel cumulative logit models to analyse ordinal outcomes for cross-country studies. This chapter summarises the main findings from these three papers and discusses how these papers can contribute to the research area on environmental behaviours.

In Papers 1 and 2, a cross-classified multilevel modelling approach is adopted to analyse the Wave 4 of the UKHLS. After all significant individual- and household-level explanatory variables are included in the final model, household, interviewer and area random effects are all significant in explaining the total individual's differences for all types of environmental behaviours. Although the magnitude of the interviewer and area effects are smaller than the household effects, they are significant at the 1% level. Interviewer effects contribute to 6.3%, 7.3%, 1.7% and 8.3% of the total unexplained variations for general, transport-, home- and purchasing-related behaviours respectively. The significance of the interviewer effect suggests that researchers should be aware of the potential interviewer's influences on the survey responses related to environmental behaviours when planning survey studies.

The findings indicate that household effects play an important role in understanding individual's environmental behaviour. They contribute to 30.0%, 18.6%, 36.0% and 28.3% of the total unexplained variations for general, transport-, home-, and purchasing-related behaviours respectively. Both individual- and household-level factors reduce the household variance. As individuals from the same household have similar sociodemographic

characteristics, personal values and environmental attitudes, individual-level variables can be treated as aggregated household-level effects. This indicates why the inclusion of individual-level variables substantially reduces the household random effect. The findings provide evidence to support the importance of individual sociodemographics, personal values, environmental concerns and attitudes, household sociodemographics, household structure, accommodation characteristics, neighbourhood characteristics and residential area in explaining different types of individual's green behaviours. For example, the results suggest that people from single-households behave differently from those who live with other people. This is particularly true for the transport- and home-related environmental behaviours. However, the results cannot confirm whether or not this is due to a selection effect. The importance of household effect suggests that government policies on environmental behaviours should not only focus on encouraging individuals to behave green but promoting environmentally friendly behaviours among different types of household.

Results from Paper 2 also provide evidence that different types of environmental behaviours are not necessarily correlated and that they can be influenced by the different individual- and household-level factors. This suggests that analysing aggregated general behaviour may not provide enough information to understand how different types of behaviours can be influenced by different individual- and household-level explanatory variables. From a researcher's point of view, disaggregating the general environmental behaviour into different specific green behaviours allows them to understand how behaviours can be affected differently. Hence, government policies and interventions should be more behaviour-specific so that they can be effectively and efficiently implemented.

Paper 3 focuses on cross-country comparison of environmental behaviours. The country-level random effect is significant for all types of behaviours. It is estimated that 2.3% of the unexplained variation for the overall environmental behaviour is due to between country heterogeneity when all the fixed effect explanatory variables are included in the final model. Among the home-, purchasing-, recycling- and transport-related behaviours, the country-level variance effect accounts for a large proportion of the random variances in explaining individuals' recycling-related behaviour. The country random effect contributes to 12.3% of the total individual's variation for recycling while it only contributes to around 2.0% to 9.0% of the total variation for the other three types of behaviours. This paper investigates how the relationship between individual's environmental attitudes and behaviours varies across countries by including a random slope term on individual's environmental attitude. The random slope terms are significant at the 1% level for all outcomes. The variation explained by the country-level random effect becomes a quadratic function of individual's environmental attitude. For all behaviours studied, as environmental attitudes increase, the

contribution of the country-level variance on the proportion of individual's differences being explained drops gradually and then rises again.

The findings from Paper 3 show that individual sociodemographics, personal and environmental values are important in understanding the individual's differences in all types of environmental behaviours. The results, on the other hand, show that different types of behaviours are influenced by different types of country-level factors. There is no consistent result among the general and the four types of behaviours in terms of the country-level explanatory variables.

Similar to the second paper, the results from Paper 3 also support the argument that home, purchasing-, recycling- and transport-related behaviours can be encouraged or discouraged by different types of individual- and country-level factors. As the findings show that these behaviours can be influenced by a variety of sociodemographics, personal values, environmental values and country-level covariates, it further confirms the importance of studying specific green behaviour rather than aggregating different types of behaviours into one measurement. Nevertheless, findings from both Paper 2 and Paper 3 are based on the analysis of separate environmental behaviours. Neither of these papers have taken the correlations between different behaviours into consideration. It is interesting to investigate multiple environmental behaviours simultaneously. Therefore, it is sensible to examine all outcomes in a multivariate approach instead of performing a series of univariate analyses (Hox, 2010; Snijders and Bosker, 2012). In order to allow all outcomes to be examined simultaneously, a multivariate multilevel modelling approach can be used. As discussed by Snijders and Bosker (2012), there are four advantages of using a multivariate approach. One advantage is that conclusion about the correlations between the outcome variables can be drawn. Secondly, it has a more explanatory powers especially when the multiple outcomes are strongly correlated. Thirdly, it is able to test the magnitudes of all the explanatory variables on all outcome variables. Finally, using a multivariate approach can also test the joint effect of an explanatory variable on several outcomes. Therefore, further research using a multivariate multilevel modelling approach is necessary. This would allow researchers to have a better understanding on how different types of environmental behaviours are correlated and how they are influenced by different factors.

Both Papers 2 and 3 demonstrate the use of multilevel cumulative ordered logit model to analyse environmental behaviours that are measured as ordinal outcomes. At present, most studies related to environmental behaviours use single-level analysis to examine ordinal outcomes. If multilevel models were considered to analyse environmental behaviours or environmental concerns, it was only for continuous outcomes or variables that were treated as continuous (for example, Marquart-Pyatt, 2012b;a; Pisano and Lubell, 2017). However, as

analysing ordinal data as continuous data can lead to severe downward biases (Hox, 2010). Hence, both Papers 2 and 3 contribute to the current research methodology for understanding environmental behaviours.

The papers in this thesis manage to address some of the unanswered research questions in the environmental behaviour literature. However, further research is necessary due to some limitations in these studies. For instance, the analysis in Papers 2 and 3 focuses on main effects only. Neither same-level nor cross-level interaction terms have been included in the final models. However, due to the computational speed and other computing restrictions, it is impossible to test the effects of these interaction terms. A more detailed analysis can only be conducted once there are more powerful computers.

All three papers analysed self-reported pro-environmental behaviours. In UKHLS and ISSP, the majority of respondents are asked to report how often they engage in different types of behaviours in interviewer-administered face-to-face surveys. As a result, the reported outcomes may be subjected to response bias (Steg, van de Berg and de Groot, 2012). Although Paper 1 and Paper 2 have accounted for the interviewer effect in the final models, measurement errors are still likely to be present in the outcomes of interest. From a survey methodology perspective, further research on collecting reliable measures of self-reported behaviours is necessary (Steg and Vlek, 2009). Meanwhile, researchers can also consider measuring people's actual behaviours (Vining and Ebreo, 2002). However, Steg, van de Berg and de Groot (2012) argue that this would result in more complicated questionnaires and it could be labour intensive and costly. Diary recordings are a popular data collection method in many research disciplines to collect data related to people's actual behaviours. Nevertheless, it is not common for researchers to use such a method to collect respondents' actual environmental behaviours (Reid, Hunter and Sutton, 2011). The combination of using a diary and mobile phone may be an alternative to the traditional pen-and-paper diary approach. With the help of mobile phone apps, completing diary becomes easier and more convenient. Therefore, it is worth exploring the possibility of using diary or other new innovative methods to measure pro-environmental behaviours.

Appendix A

A.1 Descriptive Statistics of the Final Analysis Sample Dataset (N=36,170) - Categorical Variables

	N	%
Gender		
Male	15,903	44.0
Female	20,267	56.0
Age		
16-30	7,503	20.7
31-45	9,930	27.5
46-60	9,529	26.3
61-75	7,156	19.8
76 or above	2,052	5.7
Marital status		
Married/ cohabitation	23,361	64.6
Currently not married	12,716	35.2
(Missing)	(93)	(0.3)
Employment status		
Employed	18,049	49.9
Self-employed	2,707	7.5
Unemployed	1,758	4.9
Retired	7,862	21.7
Full-time student	2,303	6.4
Others	3,490	9.6
(Missing)	(1)	(0.0)
Highest education level		
Degree	8,847	24.5
Other higher degree	4,289	11.9
A-level or equivalent	7,677	21.2
GCSE or equivalent	7,689	21.3
Other qualification	3,270	9.0
No qualification	3,964	11.0
(Missing)	(434)	(1.2)
Ethnicity		
White	31,214	86.3
Mixed	559	1.5
Asian	2,533	7.0
Black	1,216	3.4
Other	232	0.6
(Missing)	(416)	(1.2)

	N	%
Born in the UK		
Yes	31,134	86.1
No	4,117	11.4
(Missing)	(919)	2.5)
Belong to a religion		
Yes	19,088	52.8
No	17,078	47.2
(Missing)	(4)	(0.0)
Level of interest in politics		
Very	3,629	10.0
Fairly	11,902	32.9
Not very	10,093	27.9
Not at all interested	10,531	29.1
(Missing)	(15)	(0.0)
Party affiliation		
Conservatives	7,514	20.8
Labour	10,649	29.4
Liberal Democrat	2,262	6.3
Scottish National Party	772	2.1
Plaid Cymru	234	0.6
Green Party	1,117	3.1
Ulster Unionist	390	1.1
SDLP	299	0.8
Alliance Party	191	0.5
Democratic Unionist	375	1.0
Sinn Fein	273	0.8
Other party	1,198	3.3
None	7,365	20.4
Cannot vote	794	2.2
(Missing)	(2,737)	(7.6)
Involve in voluntary work		
Yes	7,286	20.1
No	28,883	79.9
(Missing)	(1)	(0.0)
Donation to charity		
Yes	25,183	69.6
No	10,971	30.3
(Missing)	(16)	(0.0)

	N	%
Believe in the effect of climate change in the UK		
UK will not be affected in the next 30 and 200 years	3,221	8.9
UK will only be affected in the next 30 years	686	1.9
UK will only be affected in the next 200 years	4,430	12.2
UK will be affected in the next 30 and 200 years	27,301	75.5
(Missing)	(532)	(1.5)
Believe green is an alternative living style		
Agree	17,992	49.7
Disagree	17,891	49.5
(Missing)	(287)	(0.8)
Thoughts about current lifestyle and the environment	t	
I'm happy with what I do at the moment	23,591	65.2
Would like to do bit more	10,967	30.3
Would like to do lots more	1,597	4.4
(Missing)	(15)	(0.0)
Ownership of car(s)		
Yes	30,875	85.4
No	5,250	14.5
(Missing)	(45)	(0.1)
Pensioner in household		
Yes	10,591	29.3
No	25,579	70.7
Children aged 0-2 in household		
Yes	3,377	9.3
No	32,793	90.7
Children aged 3-4 in household		
Yes	2,559	7.1
No	33,611	92.9
Children aged 5-11 in household		
Yes	6,822	18.9
No	29,348	81.1
Children aged 12-15 in household		
Yes	5,067	14.0
No	31,103	86.0
Household structure		
Single household without children	5,135	14.2
Single household with children	1,553	4.3
Non-single household without children	16,725	46.2
Non-single household with children	12,757	35.3

	N	%
Tenure type		
Home owned outright	11,352	31.4
Home owned with mortgage	14,721	40.7
Home social rent	5,510	15.2
Home private/ employer rented	4,199	11.6
Other	52	0.1
(Missing)	(336)	(0.9)
Dwelling type		
Detached house	9,902	27.4
Semi-detached house/ bungalow	11,527	31.9
End terraced/ terraced house/ bungalow	9,861	27.3
Flat/ maisonette	3,857	10.7
Other	283	0.8
(Missing)	(740)	(2.0)
Trash, litter or junk in street in the neighbourhood		
Yes	1006	2.8
No	34,390	95.1
(Missing)	(774)	(2.1)
Heavy traffic in street in the neighbourhood		
Yes	3,636	10.1
No	31,761	87.8
(Missing)	(773)	(2.1)
Sample composition		
GPS	24,622	68.1
Former BHPS	8,443	23.3
EMBS	3,105	8.6
Government office region		
North East	1,303	3.6
North West	3,546	9.8
Yorkshire and the Humber	2,787	7.7
East Midlands	2,714	7.5
West Midlands	2,765	7.6
East of England	3,202	8.9
London	3,891	10.8
South East	4,398	12.2
South West	3,050	8.4
Wales	2,724	7.5
Scotland	3,392	9.4
Northern Ireland	2,398	6.6

Appendix A

	N	%
Residential area		
Urban	26,967	74.6
Rural	9,203	25.4
Total	36,170	100.0

A.2 Descriptive Statistics of the Final Analysis Sample Dataset (N=36,170) - Continuous Variables

	Mean	SD	Max	Min
Individual Gross Monthly Income	1,743.18	1,667.85	15,000	0
Environmental Concern Score	19.65	5.37	36	0

A.3 Number of Responded Cases per Household

Responded individual(s) per Household	Number of Households	% Households
1	11,654	51.53
2	8,979	39.70
3	1,486	6.57
4	419	1.85
5	61	0.27
6	14	0.06
7	5	0.02
Total	22,618	100.00

A.4 Number of Interviewers per Area

Interviewer(s) per Area	Number of Areas	% Areas
1	4,629	74.57
2	990	15.95
3	312	5.03
4	118	1.90
5	64	1.03
6	33	0.53
7	27	0.43
8	12	0.19
9	13	0.21
10	4	0.06
11	4	0.06
13	1	0.02
16	1	0.02
Total	6,208	100.00

A.5 Number of Areas per Interviewer

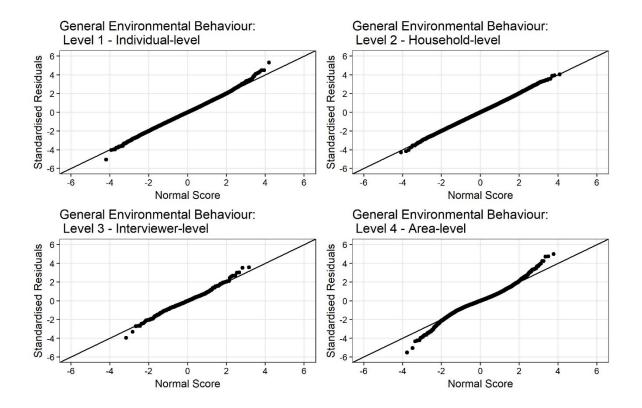
Area(s) per Interviewer	Number of Interviewers	% Interviewers
1	33	5.19
2	27	4.25
3	27	4.25
4	32	5.03
5	23	3.62
6	37	5.82
7	26	4.09
3	35	5.50
9	25	3.93
10	26	4.09
11	35	5.50
12	25	3.93
13	16	2.52
14	20	3.14
15	28	4.40
16	17	2.67
17	19	2.99
18	16	2.52
19	14	2.20
20	13	2.04
21	13	2.04
22	17	2.67
23	9	1.42
24	14	2.20
25	11	1.73
26	5	0.79
27	1	0.16
28	9	1.42
29	8	1.26
30	4	0.63
31	6	0.94
32	5	0.79
33	5	0.79
34	1	0.16
35	5	0.79
36	1	0.16
37	2	0.31
38	1	0.16
39	2	0.31

Appendix A

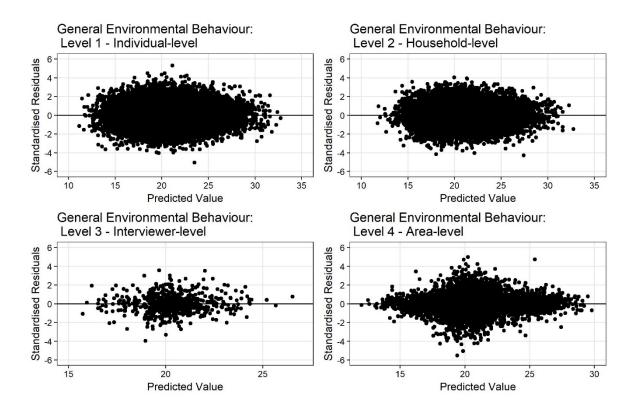
Area(s) per Interviewer	per Interviewer Number of Interviewers	
40	1	0.16
41	1	0.16
43	2	0.31
44	2	0.31
45	1	0.16
46	2	0.31
49	2	0.31
50	1	0.16
51	1	0.16
53	1	0.16
60	2	0.31
61	1	0.16
66	1	0.16
71	1	0.16
73	1	0.16
75	1	0.16
83	1	0.16
103	1	0.16
Total	636	100.00

A.6 Model Validations and Diagnostics

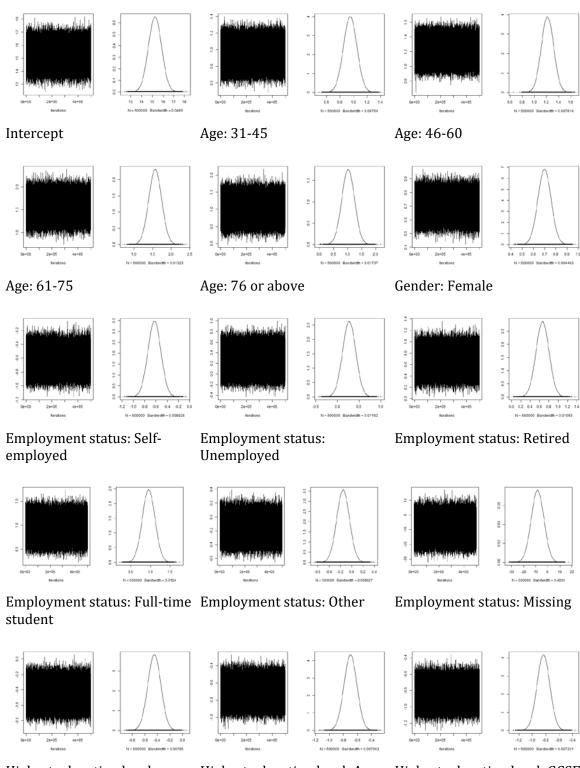
A.6.1 Normal Plots for Individual-, Household-, Interviewer- and Arealevels



A.6.2 Plot of Standardised Residuals against Fitted Values



Trace Plots of the Estimates and the Kernel Density Plots of the A.6.3 **Posterior Distribution**

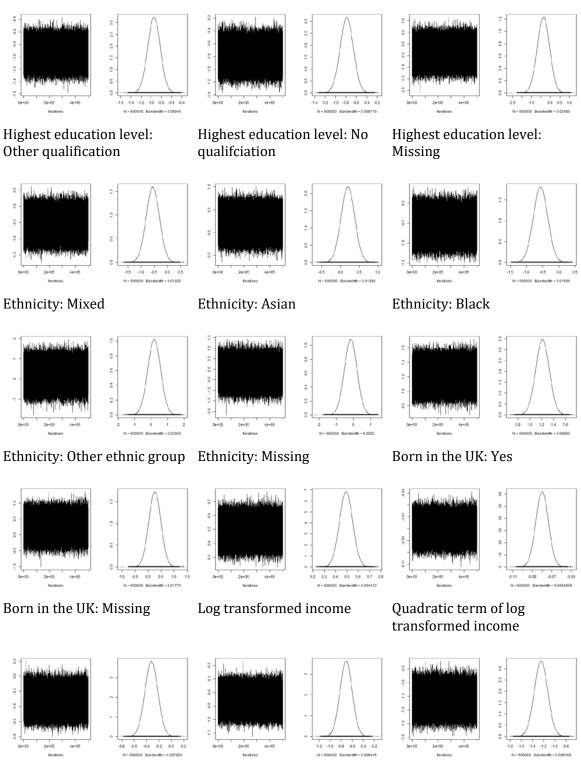


Highest education level: Other higher degree

Highest education level: Alevel or equivalent

Highest education level: GCSE or equivalent

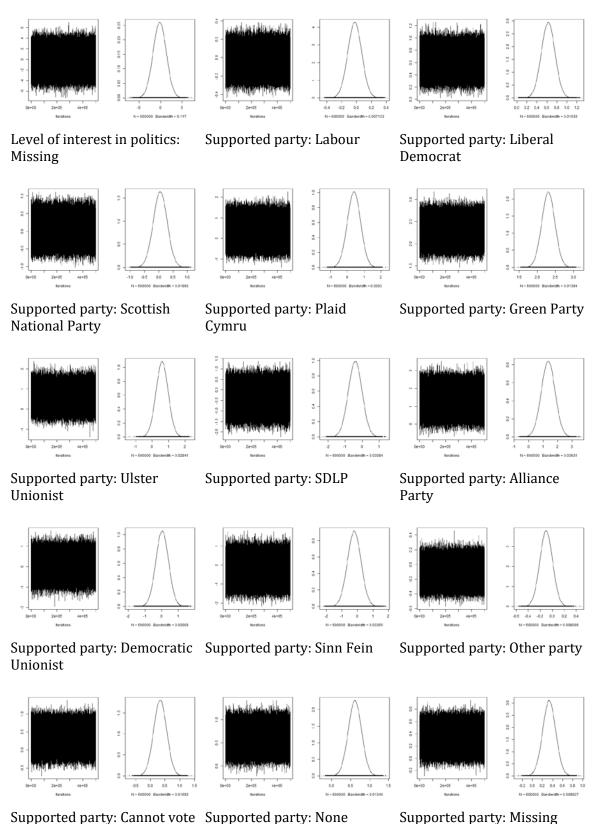
Appendix A



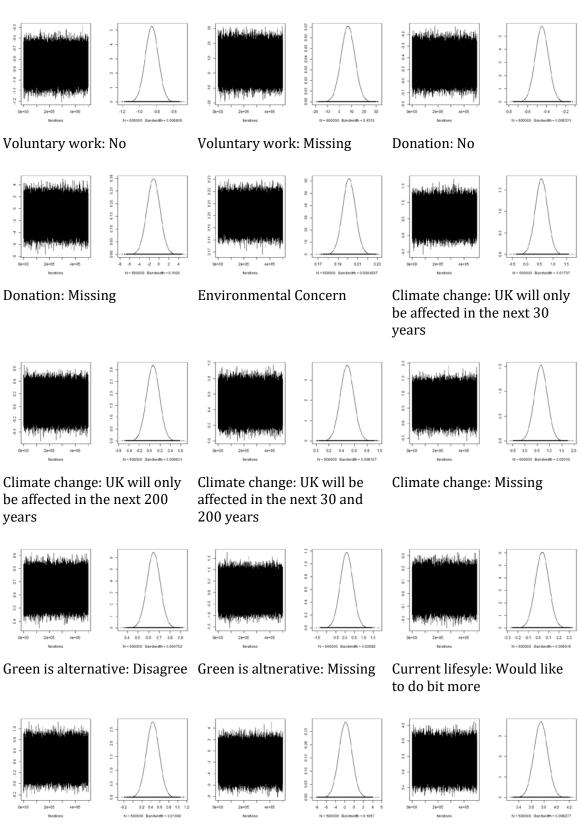
Level of interest in politics: Faily

Level of interest in politics: Not very

Level of interest in politics: Not at all interested



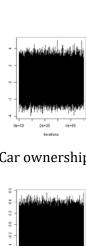
Supported party: Cannot vote Supported party: None

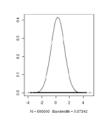


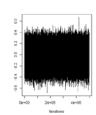
Current lifesyle: Would like to do lots more

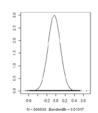
Current lifesyle: Missing

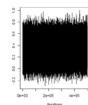
Car ownership: No

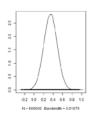








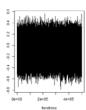


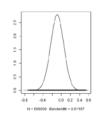


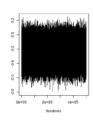
Car ownership: Missing

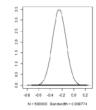
Pensioner in HH: No

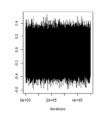
Children aged 0-2 in HH: No

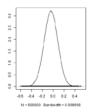








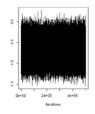


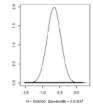


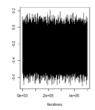
Children aged 3-4 in HH: No

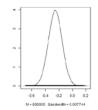
Children aged 5-11 in HH: No

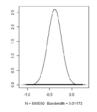
Children aged 12-15 in HH:







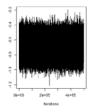


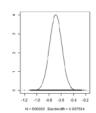


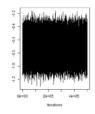
HH structure: single HH with children

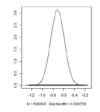
HH structure: non-single HH without children

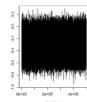
HH structure: Non-single HH with children

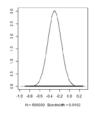








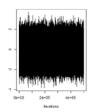


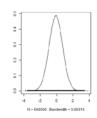


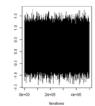
Tenure type: Home owned with mortgate

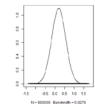
Tenure type: Home social rent

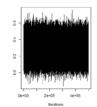
Tenure type: Home private/ employer rented

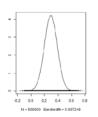










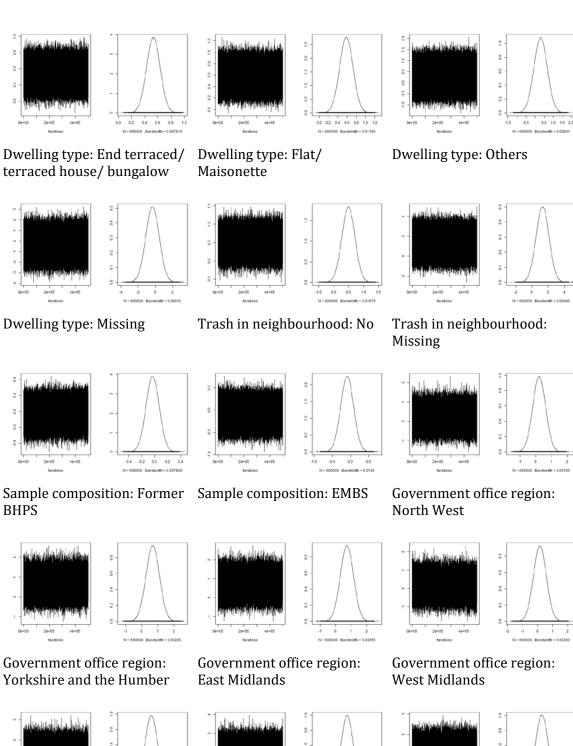


Tenure type: Other

Tenure type: Missing

Dwelling type: Semi-detached house/bungalow

Appendix A



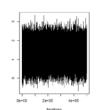
Government office region: East of England

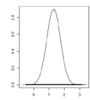
00-10 20-05 40-15

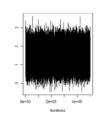
Government office region: London

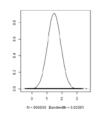
Ce=10 2e=05 4e=15 N=500000 N=500000 N=5000000 N=500000 N=5000000 N=500000 N=500000 N=500000 N=500000 N=500000 N=500000 N=5000000 N=500000 N=500000 N=500000 N=500000 N=500000 N=500000 N=5000000 N=500000 N=500000 N=500000 N=500000 N=500000 N=500000 N=500000 N=500000 N=50000 N=50000 N=50000 N=50000 N=50000 N=50000 N=500000 N=50000 N=5000 N=50000 N=50000 N=50000 N=500

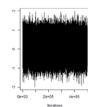
Government office region: South East

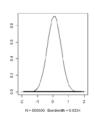






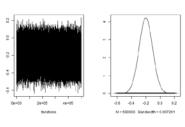




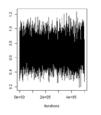


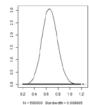
Government office region: South West

Government office region: Wales

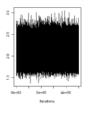


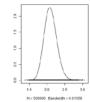
Government office region: Scotland



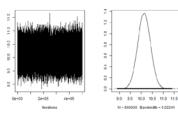


Government office region: Northern Ireland





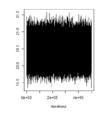
Residential area: Rural

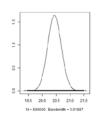


Household-level Random

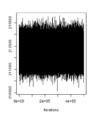
Effect

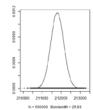
Area-level Random Effect





Interviewer-level Random Effect





DIC

Individual-level Random Effect

A.6.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
<u>Fixed Effect</u>		
Intercept	80,369	(19,875; 16,172)
Age (16-30)		
31-45	252,955	(7,764; 7,662)
46-60	269,410	(7,738; 7,638)
61-75	269,087	(7,738; 7,704)
76 or above	252,467	(7,790; 7,646)
Gender (Male)		
Female	338,773	(4,019; 4,040)
Employment status (Employed)		
Self-employed	269,049	(7,716; 7,840)
Unemployed	274,164	(7,698; 7,684)
Retired	259,005	(7,744; 7,722)
Full-time Student	281,838	(7,696; 4,280)
Other Employment Status	269,081	(4,306; 7,712)
Missing	298,657	(7,650; 4,173)
Highest education level (Degree)		
Other Higher Degree	269,211	(4,337; 7,794)
A-level or Equivalent	262,715	(7,822; 7,838)
GCSE or Equivalent	260,871	(7,674; 7,670)
Other Qualification	266,404	(7,666; 7,700)
No Qualification	256,864	(7,864; 7,838)
Missing	281,943	(4,286; 7,686)
Ethnicity (White)		
Mixed	252,690	(7,674; 7,718)
Asian	188,002	(8,134; 8,164)
Black	212,606	(7,970; 8,020)
Other Ethnic Group	227,323	(7,828; 7,792)
Missing	291,777	(4,273; 4,292)
Born in the UK (Yes)		
No	251,637	(7,906; 7,798)
Missing	280,679	(7,736; 4,240)
Individual monthly income		
Log transformed income	287,507	(7,712; 4,278)
Quadratic term of log transformed income	284,075	(7,808; 7,668)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Level of interest in politics (Very interest)		
Fairly	270,052	(7,844; 7,778)
Not very	264,179	(7,744; 7,692)
Not at all interested	260,034	(7,758; 7,666)
Missing	213,528	(7,978; 8,150)
Supported party (Conservative)		
Labour	229,062	(7,862; 7,826)
Liberal Democrat	249,408	(7,694; 7,798)
Scottish National Party	233,405	(7,890; 7,928)
Plaid Cymru	237,475	(7,906; 7,928)
Green Party	255,917	(7,790; 7,850)
Ulster Unionist	215,380	(7,896; 7,914)
SDLP	219,080	(7,912; 7,916)
Alliance Party	221,243	(7,926; 7,976)
Democratic Unionist	209,635	(8,058; 8,020)
Sinn Fein	190,024	(8,144; 8,024)
Other party	240,336	(7,720; 7,860)
Cannot vote	282,694	(7,770; 7,780)
None	249,950	(7,692; 7,640)
Missing	242,671	(7,674; 7,722)
Voluntary work in the last 12 months (Yes)		
No	252,369	(7,802; 7,706)
Missing	241,607	(7,840; 7,842)
Donation to charity in the last 12 months (Yes)		
No	246,907	(7,856; 7,818)
Missing	284,288	(7,638; 7,748)
Environmental Concern Score	259,731	(7,584; 7,656)
Believe in the effect of climate change in the UK (UK will not be affected in the next 30 and 200 years)		
UK will only be affected in the next 30 years	281,795	(7,588; 7,750)
UK will only be affected in the next 200 years	279,083	(7,686; 7,764)
UK will be affected in the next 30 and 200 years	271,299	(7,616; 7,732)
Missing	258,251	(7,714; 7,694)
Believe green is an alternative living style (Agree)		
Disagree	273,227	(7,724; 7,784)
Missing	255,689	(7,770; 7,804)

ariable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Thoughts about current lifestyle and the environm (I'm happy with what I do at the moment)	nent	
Would like to do bit more	280,797	(7,728; 7,670)
Would like to do lots more	281,702	(7,726; 7,704)
Missing	283,746	(4,273; 7,622)
Ownership of car(s) (Yes)		
No	191,898	(8,168; 8,056)
Missing	176,100	(8,398; 8,106)
Pensioner(s) in household (Yes)		
No	202,052	(8,010; 7,936)
Children aged 0-2 in household (Yes)		
No	168,733	(8,540; 8,372)
Children aged 3-4 in household (Yes)		
No	173,119	(8,254; 8,210)
Children aged 5-11 in household (Yes)		
No	164,217	(8,574; 8,394)
Children aged 12-15 in household (Yes)		
No	159,321	(8,474; 8,426)
Household structure (Single household without children)		
Single household with children	201,922	(8,036; 8,024)
Non-single household without children	213,923	(7,946; 7,922)
Non-single household with children	176,215	(8,224; 8,176)
Tenure type (Home owned outright)		
Home owned with mortgage	168,719	(8,430; 8,262)
Home social rent	178,012	(8,274; 8,274)
Home private/ employer rented	180,266	(8,230; 8,276)
Other	210,172	(8,030; 7,872)
Missing	170,163	(8,500; 8,224)
Dwelling type (Detached house)		
Semi-detached house/ bungalow	164,479	(11,967; 8,324)
End terraced/ terraced house/ bungalow	166,837	(8,302; 8,502)
Flat/ maisonette	179,170	(8,144; 8,366)
Others	196,873	(8,076; 8,086)
Missing	189,068	(8,142; 8,208)
Trash, junk and rubbish on the street in the neighbourhood (Yes)		
No	157,502	(11,994; 12,189)
Missing	185,806	(8,142; 8,160)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Sample composition (GPS)		
Former BHPS	124,507	(9,230; 8,998)
EMBS	166,286	(8,396; 8,386)
Government office region (North East)		
North West	38,917	(27,756; 32,480)
Yorkshire and the Humber	38,854	(30,646; 28,686)
East Midlands	38,490	(28,908; 29,352)
West Midlands	37,065	(31,430; 29,598)
East of England	39,685	(30,352; 28,758)
London	40,644	(30,632; 30,765)
South East	38,725	(31,703; 29,418)
South West	33,849	(36,136; 33,888)
Wales	36,784	(31,325; 29,172)
Scotland	35,201	(28,680; 32,844)
Northern Ireland	45,527	(26,154; 22,750)
Residential Area (Urban)		
Rural	136,783	(11,979; 12,534)
Random Effect		
Area	2,154	(551,070; 226,728)
Interviewer	99,599	(12,795; 16,592)
Household	17,215	(44,127; 55,120)
Individual	53,044	(27,601; 29,890)
DIC	38,479	(29,015; 37,566)

^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

A.7 Estimated Coefficients for the Final Multilevel Cross-Classified Model on Pro-Environmental Behaviour Score - A Comparison of Single and Non-Single Households

		Single Household (N = 5,135)		Non-Single Household (N = 31,035 from 17,438 Households)	
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
Intercept		14.961	(1.291)***	14.524	(0.619)***
	Individual Sociodemographic Variables				
Age (16-30)	31-45	-0.085	(0.371)	1.013	(0.104)***
	46-60	0.952	(0.359)**	1.160	(0.107)***
	61-75	1.061	(0.512)*	1.544	(0.186)***
	76 or above	0.290	(0.576)	1.217	(0.261)***
Gender (Male)	Female	0.843	(0.183)***	0.686	(0.063)***
Employment Status (Employed)	Self-employed	-0.955	(0.350)**	-0.565	(0.122)***
	Unemployed	1.190	(0.436)**	0.128	(0.162)
	Retired	0.590	(0.346).	0.644	(0.154)***
	Full-time Student	0.639	(0.679)	0.987	(0.167)***
	Other Employment Status	-1.038	(0.373)**	-0.048	(0.119)
	Missing	-	-	-8.348	(5.253)

		Single	Household	Non-Singl	e Household
		(N = 5,135)		(N = 31,035 from 17,438 Households)	
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
Highest education level (Degree)	Other Higher Degree	-0.634	(0.297)*	-0.425	(0.111)***
	A-level or Equivalent	-0.378	(0.283)	-0.735	(0.097)***
	GCSE or Equivalent	-0.953	(0.292)**	-0.827	(0.101)***
	Other Qualification	-0.735	(0.323)*	-1.005	(0.133)***
	No Qualification	-1.325	(0.320)***	-0.676	(0.139)***
	Missing	-2.059	(1.271)	-0.179	(0.338)
Ethnicity (White)	Mixed	-1.354	(0.700)	-0.476	(0.269)
	Asian	-0.616	(0.655)	0.307	(0.189)
	Black	-0.664	(0.601)	-0.573	(0.240)*
	Other Ethnic Group	0.594	(0.963)	0.083	(0.432)
	Missing	1.243	(1.586)	-0.335	(0.382)
Born in the UK (Yes)	No	1.346	(0.337)***	1.184	(0.123)***
	Missing	-1.012	(0.809)	0.360	(0.242)
Individual monthly income	Log transformed income	1.020	(0.255)***	0.442	(0.060)***
	Quadratic term of log transformed income	-0.135	(0.025)***	-0.074	(0.007)***
	<u>Individual Personal Value Variables</u>				
Level of interest in politics (Very interest)	Fairly	0.213	(0.268)	-0.421	(0.113)***
	Not very	-0.171	(0.288)	-0.802	(0.120)***
	Not at all interested	-0.832	(0.302)**	-1.329	(0.130)***
	Missing	6.473	(4.006)	-1.040	(1.650)

		Single 1	Household	Non-Single Household		
		(N =	(N = 5,135)		(N = 31,035 from 17,438 Households)	
Variable	Category	β	(S.E.)	β	(S.E.)	
(Reference Category)						
Supported party (Conservative)	Labour	0.054	(0.240)	-0.025	(0.101)	
	Liberal Democrat	0.836	(0.345)*	0.598	(0.147)***	
	Scottish National Party	0.433	(0.607)	-0.048	(0.266)	
	Plaid Cymru	2.104	(1.114)	0.182	(0.422)	
	Green Party	3.005	(0.481)***	2.187	(0.197)***	
	Ulster Unionist	-0.541	(0.927)	0.827	(0.403)*	
	SDLP	-1.687	(0.964)	-0.119	(0.443)	
	Alliance Party	-1.479	(1.166)	1.916	(0.521)***	
	Democratic Unionist	-1.470	(1.004)	0.350	(0.409)	
	Sinn Fein	-2.639	(1.329)*	0.002	(0.461)	
	Other party	-0.295	(0.296)	-0.070	(0.113)	
	Cannot vote	1.418	(1.110)	0.278	(0.227)	
	None	1.101	(0.414)**	0.494	(0.193)*	
	Missing	1.313	(0.347)***	0.178	(0.139)	
Voluntary work in the last 12 months (Yes)	No	-0.897	(0.206)***	-0.860	(0.081)***	
	Missing	-	-	6.783	(5.622)	
Donation to charity in the last 12 months (Yes)	No	-0.238	(0.200)	-0.480	(0.074)***	
	Missing	2.647	(3.341)	-1.645	(1.468)	

			Household	Non-Sing	e Household
		(N = 5,135)		(N = 31,035 from 17,438 Households)	
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
	Individual Environmental Value Variables				
Environmental concern	Environmental Concern Score	0.214	(0.017)***	0.200	(0.007)***
Believe in the effect of climate change in the	UK will only be affected in the next 30 years	2.644	(0.688)***	0.332	(0.240)
UK (UK will not be affected in the next 30 and	UK will only be affected in the next 200 years	0.172	(0.368)	0.057	(0.134)
200 years)	UK will be affected in the next 30 and 200 years	0.803	(0.301)**	0.444	(0.115)***
	Missing	0.077	(0.519)	1.064	(0.314)***
Believe green is an alternative living style	Disagree	0.464	(0.179)**	0.665	(0.066)***
(Agree)	Missing	-0.562	(0.574)	0.282	(0.426)
Thoughts about current lifestyle and the	Would like to do bit more	-0.194	(0.196)	0.060	(0.070)
environment (I'm happy with what I do at the	Would like to do lots more	0.875	(0.422)*	0.380	(0.152)*
moment)	Missing	-5.237	(2.581)*	-0.591	(1.654)
	Household Sociodemographic Variables				
Ownership of car(s) (Yes)	No	3.922	(0.198)***	3.699	(0.133)***
	Missing	-2.342	(4.196)	0.417	(0.986)
	Household Structure Variables				
Pensioner(s) in household (Yes)	No	-0.108	(0.408)	0.016	(0.143)
Children aged 0-2 in household (Yes)	No	-	-	0.388	(0.141)**
Children aged 3-4 in household (Yes)	No	-	-	-0.088	(0.145)
Children aged 5-11 in household (Yes)	No	-	-	-0.225	(0.115)*
Children aged 12-15 in household (Yes)	No	-	-	-0.042	(0.125)

		Single Household (N = 5,135)		Non-Single Household (N = 31,035 from 17,438	
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)		•		-	
Household structure (Single household with	Non-single household without children	-	-	0.383	(0.193)*
children)	Non-single household with children	-	-	0.243	(0.168)
	Household Accommodation Characteristics Varia	<u>ıbles</u>			
Tenure type (Home owned outright)	Home owned with mortgage	-0.554	(0.265)*	-0.770	(0.108)***
	Home social rent	-0.289	(0.262)	-0.877	(0.147)***
	Home private/ employer rented	-0.214	(0.300)	-0.392	(0.150)**
	Other	0.625	(1.356)	-0.430	(1.061)
	Missing	-0.025	(0.916)	0.237	(0.394)
Dwelling type (Detached house)	Semi-detached house/ bungalow	0.437	(0.264)	0.249	(0.101)*
	End terraced/ terraced house/ bungalow	0.491	(0.276)	0.504	(0.112)***
	Flat/ maisonette	0.294	(0.309)	0.699	(0.170)***
	Others	-0.651	(0.581)	0.864	(0.507)
	Missing	-4.868	(1.856)**	0.746	(0.870)
	Neighbourhood Characteristic Variables				
Trash, junk and rubbish on the street in the neighbourhood (Yes)	No	-0.554	(0.508)	0.666	(0.242)**
	Missing	4.120	(1.915)*	0.573	(0.877)

		Single 1	Household	Non-Singl	e Household
		(N =	: 5,135)	•	5 from 17,438 seholds)
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
	Sampling Design Variables				
Sample composition (GPS)	Former BHPS	-0.131	(0.219)	14.524	(0.619)***
	EMBS	0.364	(0.539)	0.018	(0.110)
Government office region (North East)	North West	0.236	(0.605)	-0.161	(0.188)
	Yorkshire and the Humber	0.767	(0.660)	0.294	(0.419)
	East Midlands	0.456	(0.653)	0.740	(0.435)
	West Midlands	0.044	(0.646)	0.827	(0.440)
	East of England	0.873	(0.640)	0.183	(0.443)
	London	1.233	(0.644)	1.359	(0.422)**
	South East	0.995	(0.605)	2.231	(0.416)***
	South West	1.468	(0.654)*	1.211	(0.411)**
	Wales	1.268	(0.686)	1.314	(0.455)**
	Scotland	-0.258	(0.640)	1.499	(0.450)***
	Northern Ireland	-0.666	(0.797)	0.237	(0.450)
Residential Area (Urban)	Rural	0.009	(0.217)	-1.430	(0.478)**

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Appendix A

A.8 Sensitivity Analysis for the Evaluation of the Impact of Lack of Weights in the Analysis

FIXED EFFECT	Category	2-level Linear Model without weight		2-level Linear Model with weights	
Variable		β	(S.E.)	β	(S.E.)
(Reference Category)					
Intercept		15.218	(0.538)***	15.218	(0.547)***
	Individual Sociodemographic Variables				
Age (16-30)	31-45	0.949	(0.101)***	0.949	(0.106)***
	46-60	1.204	(0.103)***	1.204	(0.109)***
	61-75	1.557	(0.175)***	1.557	(0.174)***
	76 or above	1.015	(0.230)***	1.015	(0.227)***
Gender <i>(Male)</i>	Female	0.698	(0.059)***	0.698	(0.059)***
Employment Status (Employed)	Self-employed	-0.611	(0.116)***	-0.611	(0.115)***
	Unemployed	0.255	(0.154)	0.255	(0.166)
	Retired	0.723	(0.142)***	0.723	(0.133)***
	Full-time Student	0.981	(0.163)***	0.981	(0.175)***
	Other Employment Status	-0.140	(0.114)	-0.140	(0.119)
	Missing	-7.776	(5.327)	-7.776	(0.279)***
Highest education level (Degree)	Other Higher Degree	-0.419	(0.105)***	-0.419	(0.105)***
	A-level or Equivalent	-0.694	(0.093)***	-0.694	(0.093)***
	GCSE or Equivalent	-0.860	(0.097)***	-0.860	(0.096)***
	Other Qualification	-0.967	(0.125)***	-0.967	(0.126)***
	No Qualification	-0.844	(0.128)***	-0.844	(0.128)***
	Missing	-0.341	(0.329)	-0.341	(0.340)

FIXED EFFECT			2-level Linear Model without weight		2-level Linear Model with weights	
Variable	Category	β	(S.E.)	β	(S.E.)	
(Reference Category)						
Ethnicity (White)	Mixed	-0.565	(0.254)*	-0.565	(0.256)*	
	Asian	0.229	(0.182)	0.229	(0.189)	
	Black	-0.477	(0.224)*	-0.477	(0.235)*	
	Other Ethnic Group	0.387	(0.399)	0.387	(0.442)	
	Missing	-0.261	(0.372)	-0.261	(0.397)	
Born in the UK (Yes)	No	1.242	(0.117)***	1.242	(0.122)***	
	Missing	0.279	(0.235)	0.279	(0.253)	
Individual monthly income	Log transformed income	0.484	(0.059)***	0.484	(0.062)***	
	Quadratic term of log transformed income	-0.079	(0.007)***	-0.079	(0.007)***	
	Individual Personal Value Variables					
Level of interest in politics (Very interest)	Fairly	-0.294	(0.106)**	-0.294	(0.106)**	
	Not very	-0.686	(0.112)***	-0.686	(0.113)***	
	Not at all interested	-1.231	(0.121)***	-1.231	(0.124)***	
	Missing	-0.357	(1.557)	-0.357	(1.441)	
Supported party (Conservative)	Labour	-0.042	(0.094)	-0.042	(0.094)	
	Liberal Democrat	0.664	(0.138)***	0.664	(0.132)***	
	Scottish National Party	-0.031	(0.247)	-0.031	(0.246)	
	Plaid Cymru	0.432	(0.397)	0.432	(0.395)	
	Green Party	2.339	(0.184)***	2.339	(0.193)***	
	Ulster Unionist	0.657	(0.370)	0.657	(0.363)	
	SDLP	-0.260	(0.401)	-0.260	(0.387)	

FIXED EFFECT			2-level Linear Model without weight		inear Model weights
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
	Alliance Party	1.531	(0.472)**	1.531	(0.464)***
	Democratic Unionist	0.090	(0.378)	0.090	(0.365)
	Sinn Fein	0.146	(0.428)	0.146	(0.432)
	Other party	-0.158	(0.106)	-0.158	(0.107)
	Cannot vote	0.258	(0.223)	0.258	(0.240)
	None	0.546	(0.178)**	0.546	(0.178)**
	Missing	0.291	(0.130)*	0.291	(0.130)*
Voluntary work in the last 12 months (Yes)	No	-0.856	(0.077)***	-0.856	(0.077)***
	Missing	5.679	(5.773)	5.679	(0.362)***
Donation to charity in the last 12 months (Yes)	No	-0.430	(0.070)***	-0.430	(0.072)***
	Missing	-1.250	(1.357)	-1.250	(1.419)
	Individual Environmental Value Variables				
Environmental concern	Environmental Concern Score	0.201	(0.007)***	0.201	(0.007)***
Believe in the effect of climate change in the	UK will only be affected in the next 30 years	0.673	(0.229)**	0.673	(0.238)**
UK (UK will not be affected in the next 30 and	UK will only be affected in the next 200 years	0.075	(0.127)	0.075	(0.130)
200 years)	UK will be affected in the next 30 and 200 years	0.518	(0.108)***	0.518	(0.113)***
	Missing	0.583	(0.265)*	0.583	(0.258)*
Believe green is an alternative living style	Disagree	0.649	(0.063)***	0.649	(0.063)***
(Agree)	Missing	-0.040	(0.342)	-0.040	(0.331)

FIXED EFFECT		2-level Linear Model without weight		2-level Linear Model with weights	
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
Thoughts about current lifestyle and the	Would like to do bit more	0.022	(0.067)	0.022	(0.067)
environment (I'm happy with what I do at the moment)	Would like to do lots more	0.431	(0.145)**	0.431	(0.152)**
	Missing	-1.736	(1.410)	-1.736	(1.508)
	Household Sociodemographic Variables				
Ownership of car(s) (Yes)	No	3.721	(0.111)***	3.721	(0.118)***
	Missing	0.036	(0.985)	0.036	(1.073)
	Household Structure Variables				
Pensioner(s) in household (Yes)	No	0.014	(0.136)	0.014	(0.137)
Children aged 0-2 in household (Yes)	No	0.412	(0.145)**	0.412	(0.144)**
Children aged 3-4 in household (Yes)	No	-0.135	(0.149)	-0.135	(0.150)
Children aged 5-11 in household (Yes)	No	-0.230	(0.118)	-0.230	(0.118)
Children aged 12-15 in household (Yes)	No	-0.048	(0.129)	-0.048	(0.128)
Household structure (Single household without children)	Single household with children	-0.723	(0.206)***	-0.723	(0.214)***
	Non-single household without children	-0.233	(0.103)*	-0.233	(0.103)*
	Non-single household with children	-0.415	(0.157)**	-0.415	(0.156)**

Appendix A

FIXED EFFECT			2-level Linear Model without weight		inear Model weights
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
	Household Accommodation Characteristics Vari	<u>iables</u>			
Tenure type (Home owned outright)	Home owned with mortgage	-0.720	(0.102)***	-0.720	(0.102)***
	Home social rent	-0.744	(0.130)***	-0.744	(0.135)***
	Home private/ employer rented	-0.338	(0.137)*	-0.338	(0.140)*
	Other	-0.071	(0.846)	-0.071	(0.858)
	Missing	0.265	(0.371)	0.265	(0.381)
Dwelling type (Detached house)	Semi-detached house/ bungalow	0.268	(0.097)**	0.268	(0.094)**
	End terraced/ terraced house/ bungalow	0.493	(0.105)***	0.493	(0.103)***
	Flat/ maisonette	0.568	(0.147)***	0.568	(0.149)***
	Others	0.305	(0.380)	0.305	(0.415)
	Missing	-0.354	(0.808)	-0.354	(0.840)
	Neighbourhood Characteristic Variables				
Trash, junk and rubbish on the street in the	No	0.405	(0.215)	0.405	(0.226)
neighbourhood (Yes)	Missing	1.148	(0.813)	1.148	(0.855)
	Sampling Design Variables				
Sample composition (GPS)	Former BHPS	-0.113	(0.089)	-0.113	(0.087)
	EMBS	-0.071	(0.176)	-0.071	(0.183)

FIXED EFFECT			inear Model ut weight	2-level Linear Model with weights	
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
Government office region (North East)	North West	0.254	(0.211)	0.254	(0.217)
	Yorkshire and the Humber	0.835	(0.219)***	0.835	(0.225)***
	East Midlands	0.592	(0.220)**	0.592	(0.225)**
	West Midlands	-0.218	(0.220)	-0.218	(0.226)
	East of England	1.074	(0.215)***	1.074	(0.217)***
	London	2.146	(0.222)***	2.146	(0.227)***
	South East	1.156	(0.207)***	1.156	(0.208)***
	South West	1.205	(0.217)***	1.205	(0.219)***
	Wales	1.360	(0.224)***	1.360	(0.227)***
	Scotland	0.276	(0.221)	0.276	(0.226)
	Northern Ireland	-1.503	(0.283)***	-1.503	(0.287)***
Residential Area (Urban)	Rural	-0.143	(0.087)	-0.143	(0.086)
RANDOM EFFECT					
		Coef.	(S.E.)	Coef.	(S.E.)
Household-level		12.762	(0.288)	12.762	(0.291)
Individual-level		20.443	(0.240)	20.443	(0.264)
Deviance		220	6932.1	220	5932.1

^{***} indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

Appendix A

A.9 Estimated Coefficients for the Final Multilevel Cross-Classified Model on Pro-Environmental Behaviour Score - A Comparison of Northern Ireland Sample and England, Wales and Scotland Sample

			Northern Ireland (N = 2,398)		, Wales and otland 33,372)
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
Intercept		7.143	(5.667)	15.447	(0.626)***
	Individual Sociodemographic Variables				
Age (16-30)	31-45	2.001	(0.393)***	0.874	(0.103)***
	46-60	2.310	(0.394)***	1.146	(0.105)***
	61-75	2.897	(0.653)***	1.496	(0.179)***
	76 or above	1.971	(0.853)*	0.960	(0.235)***
Gender (Male)	Female	0.887	(0.225)***	0.681	(0.061)***
Employment Status (Employed)	Self-employed	-0.742	(0.459)	-0.629	(0.119)***
	Unemployed	0.273	(0.580)	0.284	(0.157)
	Retired	0.407	(0.552)	0.666	(0.144)***
	Full-time Student	0.172	(0.604)	1.001	(0.168)***
	Other Employment Status	-0.254	(0.392)	-0.151	(0.117)
	Missing	-	<i>(-)</i>	-8.428	(5.274)

			Northern Ireland (N = 2,398)		, Wales and otland
			,,	(N =	33,372)
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
Highest education level (Degree)	Other Higher Degree	-0.042	(0.452)	-0.476	(0.106)***
	A-level or Equivalent	-0.651	(0.376)	-0.709	(0.095)***
	GCSE or Equivalent	-0.316	(0.371)	-0.880	(0.099)***
	Other Qualification	-0.877	(0.491)	-0.959	(0.127)***
	No Qualification	-1.348	(0.448)**	-0.710	(0.132)***
	Missing	0.816	(1.012)	-0.916	(0.390)*
Ethnicity (White)	Mixed	4.598	(2.388)	-0.612	(0.252)*
	Asian	3.052	(2.378)	0.178	(0.183)
	Black	7.508	(5.459)	-0.605	(0.222)**
	Other Ethnic Group	10.150	(5.203)	0.127	(0.394)
	Missing	-0.119	(0.588)	0.500	(0.500)
Born in the UK (Yes)	No	0.766	(0.535)	1.243	(0.118)***
	Missing	0.103	(0.443)	0.349	(0.273)
Individual monthly income	Log transformed income	0.352	(0.221)	0.503	(0.061)***
	Quadratic term of log transformed income	-0.070	(0.027)**	-0.081	(0.007)***
	<u>Individual Personal Value Variables</u>				
Level of interest in politics (Very interest)	Fairly	-0.535	(0.517)	-0.310	(0.106)**
	Not very	-0.756	(0.508)	-0.709	(0.113)***
	Not at all interested	-1.336	(0.517)**	-1.241	(0.123)***
	Missing	-1.552	(3.042)	0.999	(1.751)

			2,398) So		and, Wales and Scotland	
				(N =	33,372)	
Variable	Category	β	(S.E.)	β	(S.E.)	
(Reference Category)						
Supported party (Conservative)	Labour	-	(-)	-0.033	(0.093)	
	Liberal Democrat	-	<i>(-)</i>	0.607	(0.136)***	
	Scottish National Party	12.566	(7.458)	0.033	(0.244)	
	Plaid Cymru	-	<i>(-)</i>	0.369	(0.395)	
	Green Party	9.155	(5.415)	2.215	(0.186)***	
	Ulster Unionist	5.904	(5.380)	-	<i>(-)</i>	
	SDLP	4.985	(5.382)	-	<i>(-)</i>	
	Alliance Party	6.598	(5.390)	-	<i>(-)</i>	
	Democratic Unionist	5.498	(5.381)	-	<i>(-)</i>	
	Sinn Fein	5.466	(5.382)	-	<i>(-)</i>	
	Other party	5.629	(5.375)	-0.131	(0.107)	
	Cannot vote	6.193	(5.416)	0.340	(0.228)	
	None	5.873	(5.434)	0.626	(0.178)***	
	Missing	4.303	(5.415)	0.361	(0.130)**	
Voluntary work in the last 12 months (Yes)	No	-0.690	(0.288)*	-0.868	(0.078)***	
	Missing	-	<i>(-)</i>	6.831	(5.641)	
Donation to charity in the last 12 months (Yes)	No	-0.349	(0.293)	-0.460	(0.072)***	
	Missing	-2.742	(5.497)	-1.024	(1.377)	

		Northe	rn Ireland	England, Wales	
		(N = 2,398)		Scotland	
		-	-	(N =	33,372)
Variable	Category	β	(S.E.)	β	(S.E.)
(Reference Category)					
	Individual Environmental Value Variables				
Environmental concern	Environmental Concern Score	0.158	(0.025)***	0.204	(0.007)***
Believe in the effect of climate change in the UK (UK will not be affected in the next 30 and 200 years)	UK will only be affected in the next 30 years	1.269	(0.792)	0.511	(0.236)*
	UK will only be affected in the next 200 years	0.376	(0.453)	0.030	(0.130)
	UK will be affected in the next 30 and 200 years	0.866	(0.387)*	0.451	(0.111)***
	Missing	0.962	(0.797)	0.621	(0.278)*
Believe green is an alternative living style	Disagree	0.149	(0.230)	0.683	(0.064)***
(Agree)	Missing	1.267	(0.982)	-0.084	(0.358)
Thoughts about current lifestyle and the	Would like to do bit more	0.324	(0.254)	0.010	(0.068)
environment (I'm happy with what I do at the	Would like to do lots more	0.416	(0.601)	0.431	(0.147)**
moment)	Missing	-	<i>(-)</i>	-1.832	(1.393)
	Household Sociodemographic Variables				
Ownership of car(s) (Yes)	No	3.013	(0.432)***	3.798	(0.111)***
	Missing	-14.121	(6.288)*	0.487	(0.971)
	Household Structure Variables				
Pensioner(s) in household (Yes)	No	-0.673	(0.476)	0.020	(0.138)
Children aged 0-2 in household (Yes)	No	0.797	(0.526)	0.307	(0.146)*
Children aged 3-4 in household (Yes)	No	0.757	(0.529)	-0.150	(0.150)
Children aged 5-11 in household (Yes)	No	0.399	(0.411)	-0.292	(0.119)*
Children aged 12-15 in household (Yes)	No	-0.135	(0.440)	-0.041	(0.130)

		Northern Ireland (N = 2,398)		England, Wales and Scotland (N = 33,372)	
Variable					
	Category	β	(S.E.)	β	(S.E.)
(Reference Category)		2.121	(0, (0,0)	0.500	CO. O. O. O. Market
Household structure (Single household with	Non-single household without children	0.421	(0.698)	-0.733	(0.209)***
children)	Non-single household with children	0.378	(0.376)	-0.286	(0.104)**
	Household Accommodation Characteristics Van	<u> iables</u>			
Tenure type (Home owned outright)	Home owned with mortgage	-0.341	(0.351)	-0.728	(0.103)***
	Home social rent	-1.282	(0.507)*	-0.692	(0.131)***
	Home private/ employer rented	0.240	(0.489)	-0.354	(0.138)*
	Other	5.479	(5.416)	-0.244	(0.834)
	Missing	4.007	(2.053)	0.107	(0.367)
Dwelling type (Detached house)	Semi-detached house/ bungalow	0.848	(0.338)*	0.248	(0.098)*
	End terraced/terraced house/bungalow	0.473	(0.376)	0.531	(0.107)***
	Flat/ maisonette	2.539	(0.851)**	0.510	(0.148)***
	Others	1.564	(2.244)	0.239	(0.376)
	Missing	-1.001	(5.541)	-0.431	(0.795)
	Neighbourhood Characteristic Variables				
Trash, junk and rubbish on the street in the neighbourhood (Yes)	No	0.181	(0.698)	0.482	(0.230)*
	Missing	2.329	(5.662)	1.312	(0.803)

	Category	Northern Ireland (N = 2,398)		England, Wales and Scotland (N = 33,372)	
Variable		β	(S.E.)	β	(S.E.)
(Reference Category)					
	Sampling Design Variables				
Sample composition (GPS)	Former BHPS	-0.247	(0.281)	0.014	(0.109)
	EMBS	-	<i>(-)</i>	-0.077	(0.178)
Government office region (North East)	North West	-	<i>(-)</i>	0.218	(0.402)
	Yorkshire and the Humber	-	<i>(-)</i>	0.664	(0.419)
	East Midlands	-	<i>(-)</i>	0.708	(0.424)
	West Midlands	-	<i>(-)</i>	0.145	(0.428)
	East of England	-	<i>(-)</i>	1.244	(0.405)**
	London	-	<i>(-)</i>	1.992	(0.400)***
	South East	-	<i>(-)</i>	1.103	(0.394)**
	South West	-	<i>(-)</i>	1.277	(0.437)**
	Wales	-	<i>(-)</i>	1.448	(0.433)***
	Scotland	-	<i>(-)</i>	0.042	(0.432)
	Northern Ireland	-	<i>(-)</i>	-	(-)
Residential Area (Urban)	Rural	-0.993	(0.319)**	-0.125	(0.099)

^{***} indicates *p*-value ≤ 0.001 ; ** indicates *p*-value ≤ 0.01 ; * indicates *p*-value ≤ 0.05

Appendix B

B.1 Number of Responded Cases per Household

Responded individual(s)	Trans	port	Ног	ne	Purch	asing
per Household	N	%	N	%	N	%
1	10,806	52.8	11,780	49.8	12,205	52.4
2	7,973	39.0	9,598	40.6	9,154	39.3
3	1,266	6.2	1,670	7.1	1,468	6.3
4	345	1.7	498	2.1	399	1.7
5	58	0.3	72	0.3	54	0.2
6	10	0.0	18	0.1	13	0.1
7	6	0.0	9	0.0	5	0.0
Total	20,464	100	23,645	100	23,298	100

B.2 Number of Interviewers per Area

Interviewer(s) per Area	Trans	sport	Но	me	Purch	asing
	N	%	N	%	N	%
1	4,372	74.5	4,736	74.5	4,689	74.5
2	961	16.4	1,010	15.9	998	15.9
3	282	4.8	321	5.1	318	5.1
4	104	1.8	121	1.9	121	1.9
5	61	1.0	70	1.1	68	1.1
6	29	0.5	33	0.5	33	0.5
7	27	0.5	27	0.4	28	0.4
8	9	0.2	13	0.2	14	0.2
9	11	0.2	14	0.2	11	0.2
10	4	0.1	4	0.1	4	0.1
11	3	0.1	5	0.1	5	0.1
13	1	0.0	1	0.0	1	0.0
15	1	0.0	0	0.0	0	0.0
16	0	0.0	1	0.0	1	0.0
Total	5,865	100	6,356	100	6,291	100

B.3 Number of Areas per Interviewer

Area(s) per Interviewer	Tran	sport	Но	ome	Purc	hasing
	N	%	N	%	N	%
1	31	4.91	34	5.34	34	5.35
2	31	4.91	25	3.92	24	3.77
3	26	4.11	28	4.40	29	4.56
4	34	5.38	29	4.55	29	4.56
5	30	4.75	22	3.45	21	3.30
6	39	6.17	38	5.97	39	6.13
7	28	4.43	25	3.92	27	4.25
8	36	5.70	31	4.87	31	4.87
9	27	4.27	27	4.24	27	4.25
10	27	4.27	25	3.92	23	3.62
11	26	4.11	33	5.18	33	5.19
12	30	4.75	29	4.55	30	4.72
13	20	3.16	14	2.20	15	2.36
14	19	3.01	17	2.67	17	2.67
15	24	3.80	26	4.08	29	4.56
16	14	2.22	25	3.92	20	3.14
17	15	2.37	14	2.20	19	2.99
18	23	3.64	17	2.67	18	2.83
19	16	2.53	17	2.67	13	2.04
20	10	1.58	10	1.57	11	1.73
21	18	2.85	17	2.67	20	3.14
22	11	1.74	14	2.20	13	2.04
23	11	1.74	9	1.41	6	0.94
24	7	1.11	15	2.35	14	2.20
25	7	1.11	12	1.88	11	1.73
26	9	1.42	8	1.26	8	1.26
27	4	0.63	3	0.47	4	0.63
28	6	0.95	7	1.10	7	1.10
29	7	1.11	8	1.26	8	1.26
30	4	0.63	3	0.47	2	0.31
31	3	0.47	4	0.63	4	0.63
32	5	0.79	6	0.94	7	1.10
33	3	0.47	5	0.78	5	0.79
34	1	0.16	3	0.47	3	0.47
35	4	0.63	5	0.78	3	0.47
36	3	0.47	1	0.16	1	0.16
37	1	0.16	3	0.47	3	0.47
38	2	0.32	1	0.16	2	0.31

Appendix B

Area(s) per Interviewer	Tran	sport	Но	me	Purch	asing
	N	%	N	%	N	%
39	1	0.16	0	0.00	1	0.16
40	1	0.16	2	0.31	1	0.16
41	0	0.00	2	0.31	3	0.47
42	3	0.47	0	0.00	0	0.00
43	0	0.00	3	0.47	2	0.31
44	2	0.32	2	0.31	1	0.16
45	1	0.16	0	0.00	0	0.00
46	1	0.16	3	0.47	3	0.47
47	0	0.00	1	0.16	1	0.16
48	1	0.16	0	0.00	1	0.16
49	1	0.16	1	0.16	0	0.00
50	1	0.16	0	0.00	1	0.16
51	0	0.00	2	0.31	1	0.16
52	1	0.16	1	0.16	1	0.16
53	0	0.00	1	0.16	1	0.16
56	1	0.16	0	0.00	0	0.00
59	2	0.32	0	0.00	0	0.00
61	0	0.00	2	0.31	2	0.31
63	0	0.00	1	0.16	1	0.16
66	0	0.00	1	0.16	1	0.16
71	1	0.16	1	0.16	1	0.16
73	1	0.16	1	0.16	1	0.16
80	0	0.00	0	0.00	1	0.16
81	0	0.00	1	0.16	0	0.00
82	1	0.16	0	0.00	0	0.00
84	0	0.00	1	0.16	1	0.16
100	1	0.16	0	0.00	0	0.00
101	0	0.00	0	0.00	1	0.16
106	0	0.00	1	0.16	0	0.00
Total	632	100	637	100	636	100

B.4 Descriptive Statistics of the Final Analysis Sample Datasets for Three Different Outcomes - Categorical Variables

	Trans	Transport (N=32,322)		Home		asing
	(N=32)			509)	(N=36)	,896)
	N	%	N	%	N	%
Gender						
Male	14,548	45.0	16,976	44.1	15,965	43.3
Female	17,774	55.0	21,533	55.9	20,931	56.7
Age						
16-30	6,698	20.7	8,093	21.0	7,424	20.1
31-45	8,996	27.8	10,260	26.6	10,007	27.3
46-60	8,604	26.6	9,964	25.9	9,705	26.3
61-75	6,302	19.5	7,639	19.8	7,374	20.0
76 or above	1,722	5.3	2,553	6.6	2,386	6.5
Marital status						
Married/ cohabitation	21,202	65.6	24,384	63.3	23,622	64.0
Currently not married	11,039	34.2	14,028	36.4	13,182	35.
(Missing)	(81)	(0.3)	(97)	(0.3)	(92)	(0.2
Employment status						
Employed	16,639	51.5	18,543	48.2	17,978	48.
Self-employed	2,548	7.9	2,809	7.3	2,699	7.3
Unemployed	1,452	4.5	1,913	5.0	1,804	4.9
Retired	6,814	21.1	8,744	22.7	8,385	22.
Full-time student	2,024	6.3	2,608	6.8	2,272	6.2
Others	2,844	8.8	3,890	10.1	3,756	10.
(Missing)	(1)	(0.0)	(2)	(0.0)	(2)	(0.0
Highest education level						
Degree	8,178	25.3	9,129	23.7	8,873	24.
Other higher degree	3,884	12.0	4,478	11.6	4,340	11.
A-level or equivalent	6,934	21.5	8,100	21.0	7,705	20.9
GCSE or equivalent	6,814	21.1	8,177	21.2	7,783	21.
Other qualification	2,837	8.8	3,580	9.3	3,428	9.3
No qualification	3,287	10.2	4,566	11.9	4,340	11.
(Missing)	(388)	(1.2)	(479)	(1.2)	(427)	(1.2
Ethnicity						
White	27,971	86.5	33,227	86.3	31,900	86.
Mixed	483	1.5	597	1.6	575	1.6
Asian	2,279	7.1	2,699	7.0	2,557	6.9
Black	1,022	3.2	1,288	3.3	1,229	3.3
Other	186	0.6	243	0.6	231	0.6
(Missing)	(381)	(1.2)	(455)	(1.2)	(404)	(1.1

	Transport		Hon	ne	Purcha	asing
	(N=32,322)		(N=38,509)		(N=36,	896)
	N	%	N	%	N	%
Born in the UK						
Yes	27,824	86.1	33,151	86.1	31,801	86.2
No	3,653	11.3	4,371	11.4	4,186	11.3
(Missing)	(845)	(2.6)	(987)	(2.6)	(909)	(2.5)
Belong to a religion						
Yes	16,982	52.5	20,422	53.0	19,648	53.3
No	15,336	47.4	18,083	47.0	17,244	46.7
(Missing)	(4)	(0.0)	(4)	(0.0)	(4)	(0.0)
Level of interest in politics						
Very	3,262	10.1	3,854	10.0	3,683	10.0
Fairly	10,796	33.4	12,514	32.5	12,046	32.6
Not very	9,006	27.9	10,718	27.8	10,287	27.9
Not at all interested	9,243	28.6	11,405	29.6	10,865	29.4
(Missing)	(15)	(0.0)	(18)	(0.0)	(15)	(0.0)
Party affiliation						
Conservatives	6,882	21.3	7,862	20.4	7,579	20.5
Labour	9,426	29.2	11,327	29.4	10,904	29.6
Liberal Democrat	2,031	6.3	2,373	6.2	2,292	6.2
Scottish National Party	706	2.2	806	2.1	787	2.1
Plaid Cymru	207	0.6	259	0.7	249	0.7
Green Party	1,025	3.2	1,176	3.1	1,137	3.1
Ulster Unionist	353	1.1	414	1.1	406	1.1
SDLP	267	0.8	323	0.8	314	0.9
Alliance Party	180	0.6	196	0.5	194	0.5
Democratic Unionist	334	1.0	397	1.0	391	1.1
Sinn Fein	254	0.8	296	0.8	283	0.8
Other party	1,060	3.3	1,281	3.3	1,221	3.3
None	6,489	20.1	7,914	20.6	7,575	20.5
Cannot vote	694	2.1	955	2.5	794	2.2
(Missing)	(2,414)	(7.5)	(2,930)	(7.6)	(2,770)	(7.5
Involve in voluntary work						
Yes	6,572	20.3	7,628	19.8	7,300	19.8
No	25,750	79.7	30,881	80.2	29,595	80.2
(Missing)	(0)	(0.0)	(0)	(0.0)	(1)	(0.0
Donation to charity						
Yes	22,716	70.3	26,566	69.0	25,614	69.4
No	9,592	29.7	11,927	31.0	11,268	30.5
(Missing)	(14)	(0.0)	(16)	(0.0)	(14)	(0.0

	Transport		Hon	ne	Purcha	asing
	(N=32,322)		(N=38)	(N=38,509)		,896)
	N	%	N	%	N	%
Believe in the effect of climate change in the UK						
UK will not be affected in the next 30 and 200 years	2,858	8.8	3,478	9.0	3,288	8.9
UK will only be affected in the next 30 years	594	1.8	743	1.9	713	1.9
UK will only be affected in the next 200 years	3,981	12.3	4,724	12.3	4,471	12.1
UK will be affected in the next 30 and 200 years	24,443	75.6	28,915	75.1	27,816	75.4
(Missing)	(446)	(1.4)	(649)	(1.7)	(608)	(1.6)
Believe green is an alternative living style						
Agree	15,947	49.3	19,320	50.2	18,430	50.0
Disagree	16,139	49.9	18,820	48.9	18,127	49.1
(Missing)	(236)	(0.7)	(369)	(1.0)	(339)	(0.9)
Thoughts about current lifestyle and the environment						
I'm happy with what I do at the moment	20,999	65.0	25,151	65.3	24,072	65.2
Would like to do bit more	9,901	30.6	11,597	30.1	11,141	30.2
Would like to do lots more	1,407	4.4	1,736	4.5	1,662	4.5
(Missing)	(15)	(0.0)	(25)	(0.1)	(21)	(0.1)
Ownership of car(s)						
Yes	28,343	87.7	32,240	83.7	30,893	83.7
No	3,938	12.2	6,220	16.2	5,960	16.2
(Missing)	(41)	(0.1)	(49)	(0.1)	(43)	(0.1)
Pensioner in household						
Yes	9,283	28.7	11,662	30.3	11,139	30.2
No	23,039	71.3	26,847	69.7	25,757	69.8
Children aged 0-2 in household						
Yes	2,973	9.2	3,498	9.1	3,385	9.2
No	29,349	90.8	35,011	90.9	33,511	90.8
Children aged 3-4 in household						
Yes	2,289	7.1	2,662	6.9	2,553	6.9
No	30,033	92.9	35,847	93.1	34,343	93.1
Children aged 5-11 in househol	d					
Yes	6,097	18.9	7,134	18.5	6,852	18.6
No	26,225	81.1	31,375	81.5	30,044	81.4

	Transport		Hon	ne	Purcha	asing
	(N=32,322)		(N=38)	,509)	(N=36)	896)
	N	%	N	%	N	%
Children aged 12-15 in househo	ld					
Yes	4,570	14.1	5,367	13.9	5,082	13.8
No	27,752	85.9	33,142	86.1	31,814	86.2
Household structure						
Single household without children	4,388	13.6	5,720	14.9	5,571	15.1
Single household with children	1,292	4.0	1,669	4.3	1,598	4.3
Non-single household without children	15,097	46.7	17,742	46.1	16,985	46.0
Non-single household with children	11,545	35.7	13,378	34.7	12,742	34.5
Tenure type						
Home owned outright	10,158	31.4	12,159	31.6	11,639	31.5
Home owned with mortgage	13,644	42.2	15,280	39.7	14,666	39.7
Home social rent	4,470	13.8	6,199	16.1	5,901	16.0
Home private/ employer rented	3,709	11.5	4,464	11.6	4,305	11.7
Other	44	0.1	53	0.1	54	0.1
(Missing)	(297)	(0.9)	(354)	(0.9)	(331)	(0.9)
Dwelling type						
Detached house	9,015	27.9	10,438	27.1	9,979	27.0
Semi-detached house/ bungalow	10,408	32.2	12,201	31.7	11,668	31.6
End terraced/ terraced house/ bungalow	8,596	26.6	10,580	27.5	10,129	27.5
Flat/ maisonette	3,312	10.2	4,183	10.9	4,048	11.0
Other	238	0.7	331	0.9	319	0.9
(Missing)	(663)	(2.1)	(776)	(2.0)	(753)	(2.0)
Trash, litter or junk in street in the neighbourhood						
Yes	860	2.7	1,087	2.8	1,045	2.8
No	30,767	95.2	36,613	95.1	35,064	95.0
(Missing)	(695)	(2.2)	(809)	(2.1)	(787)	(2.1)
Heavy traffic in street in the neighbourhood						
Yes	3,171	9.8	3,917	10.2	3,724	10.1
No	28,457	88.0	33,784	87.7	32,386	87.8
(Missing)	(694)	(2.1)	(808)	(2.1)	(786)	(2.1)

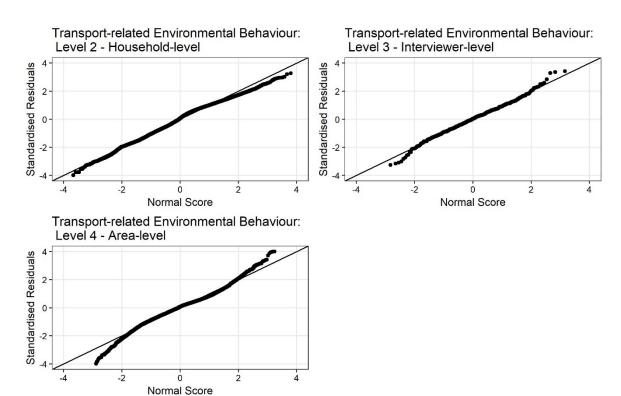
	Transport		Hor	ne	Purch	asing
	(N=32	(N=32,322)		,509)	(N=36	,896)
	N	%	N	%	N	%
Government office region						
North East	1,140	3.5	1,429	3.7	1,361	3.7
North West	3,319	10.3	3,770	9.8	3,629	9.8
Yorkshire and the Humber	2,436	7.5	2,999	7.8	2,828	7.7
East Midlands	2,414	7.5	2,881	7.5	2,728	7.4
West Midlands	2,486	7.7	2,963	7.7	2,817	7.6
East of England	2,893	9.0	3,375	8.8	3,223	8.7
London	3,389	10.5	4,114	10.7	3,937	10.7
South East	4,058	12.6	4,648	12.1	4,481	12.1
South West	2,796	8.7	3,226	8.4	3,111	8.4
Wales	2,327	7.2	2,972	7.7	2,828	7.7
Scotland	3,068	9.5	3,565	9.3	3,472	9.4
Northern Ireland	2,166	6.7	2,567	6.7	2,481	6.7
Residential area						
Urban	24,004	74.3	28,651	74.4	27,438	74.4
Rural	8,318	25.7	9,858	25.6	9,458	25.6
Sample composition						
GPS	21,935	67.9	26,230	68.1	25,156	68.2
Former BHPS	7,664	23.7	8,974	23.3	8,606	23.3
EMBS	2,723	8.4	3,305	8.6	3,134	8.5
Total	32,322	100.0	38,509	100.0	36,896	100.0

B.5 Descriptive Statistics of the Final Analysis Sample Datasets for Three Different Outcomes – Continuous Variables

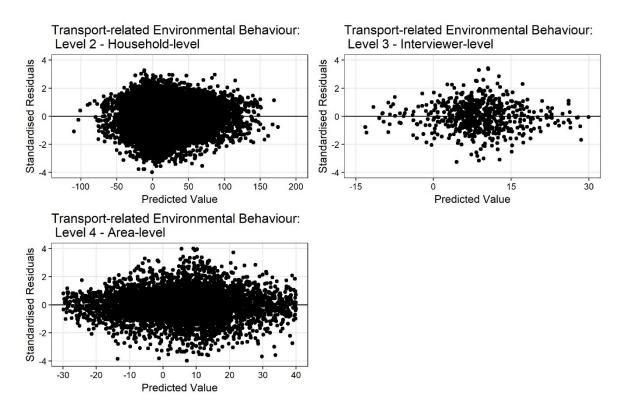
	Mean	SD	Max	Min
Transport				
Individual Gross Monthly Income	1,789.06	1,705.84	0	15,000
Environmental Concern Score	19.70	5.38	0	36
Home				
Individual Gross Monthly Income	1,708.93	1,646.21	0	15,000
Environmental Concern Score	19.59	5.37	0	36
Purchasing				
Individual Gross Monthly Income	1,724.50	1,642.87	0	15,000
Environmental Concern Score	19.63	5.37	0	36

B.6 Transport-related Environmental Behaviour: Model Validations and Diagnostics

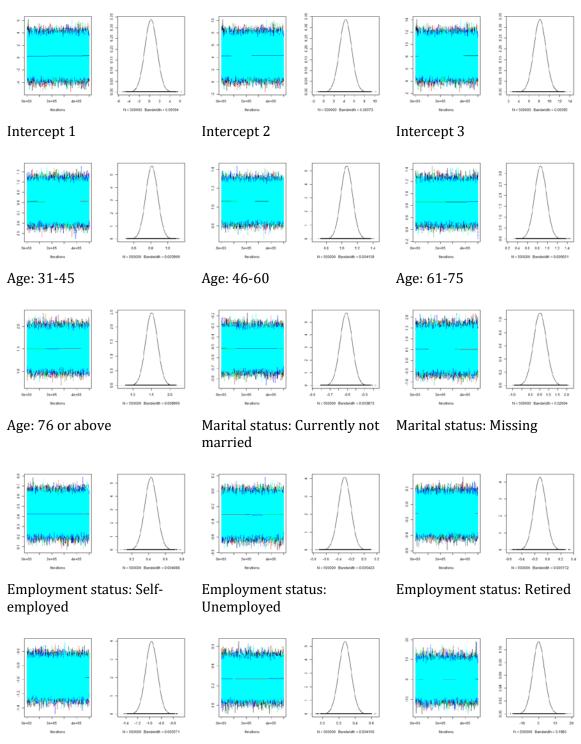
B.6.1 Normal Plots for Household-, Interviewer- and Area-levels



B.6.2 Plot of Standardised Residuals against Fitted Values

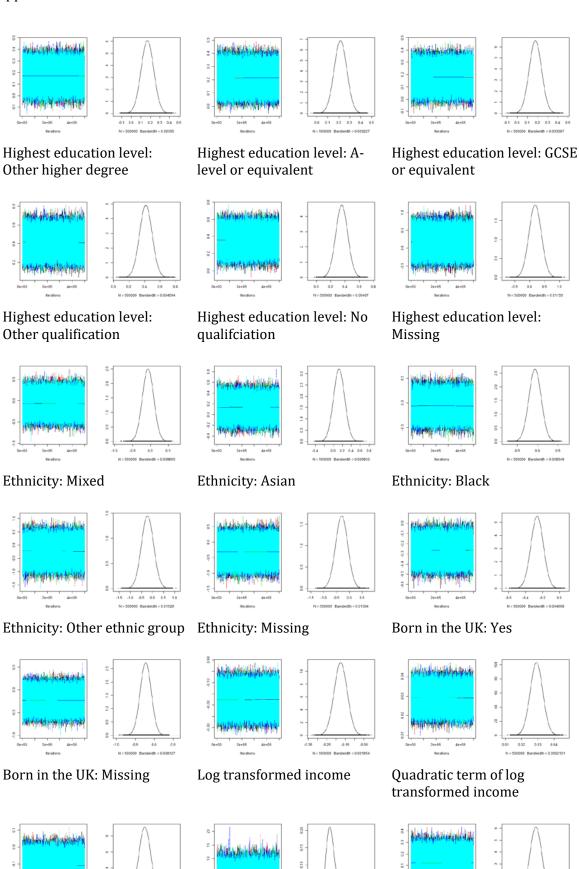


Trace Plots of the Estimates and the Kernel Density Plots of the **B.6.3 Posterior Distribution**



Employment status: Full-time Employment status: Other student

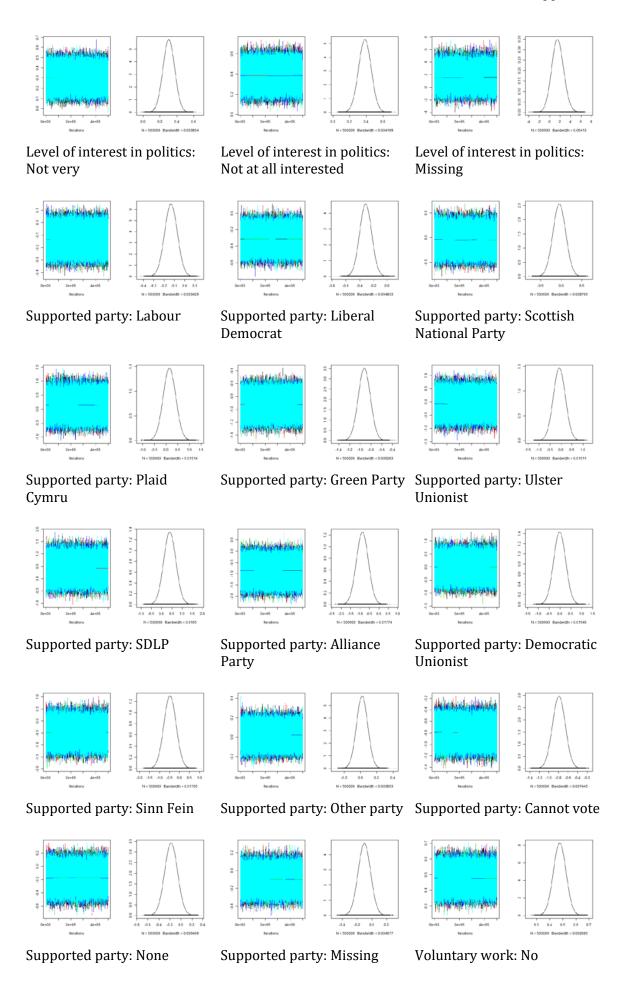
Employment status: Missing



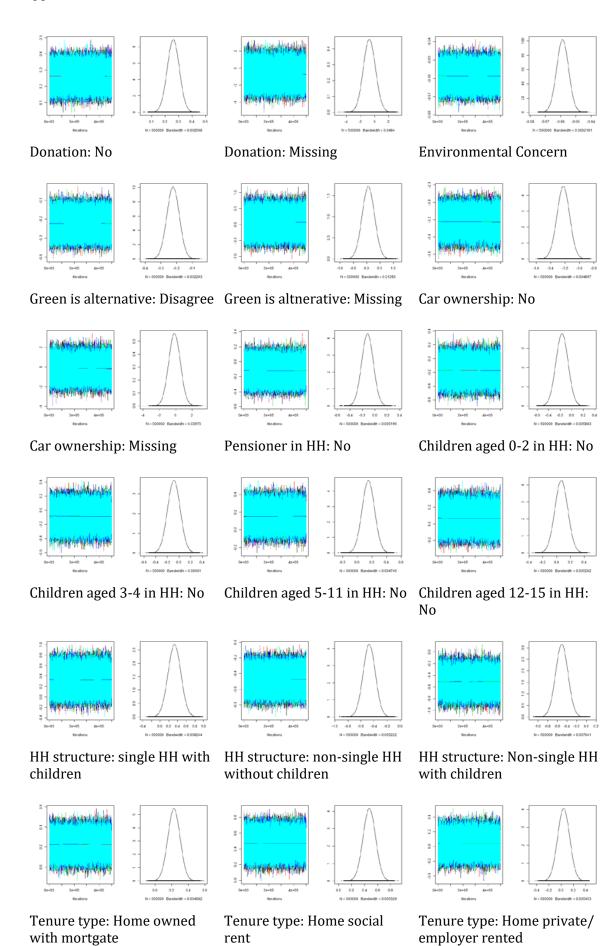
Belong to a religion: No

Belong to a religion: Missing

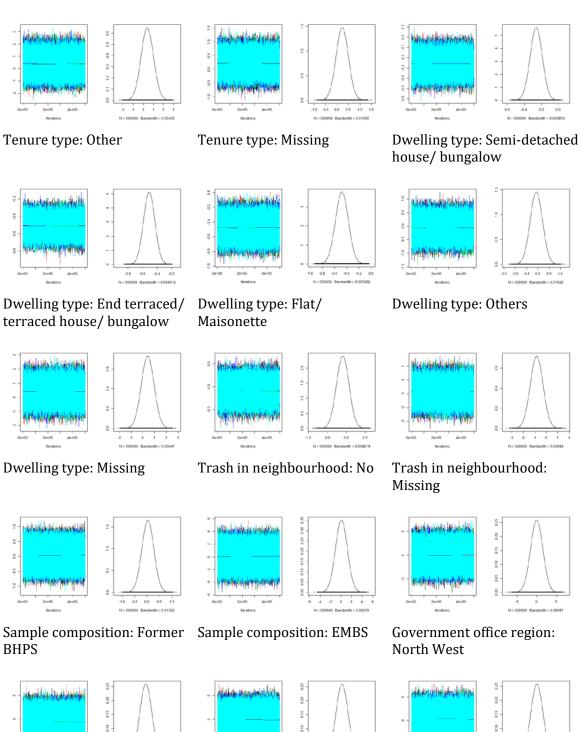
Level of interest in politics: Faily



239



240

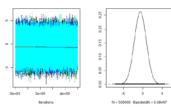


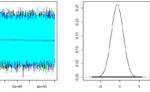
Government office region: Yorkshire and the Humber

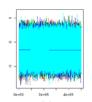
Government office region: East Midlands

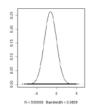
Government office region: West Midlands

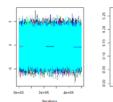
Appendix B

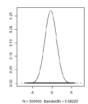






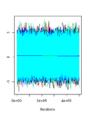


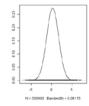




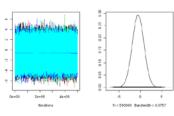
Government office region: East of England

Government office region: London

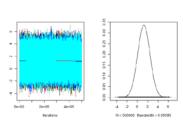




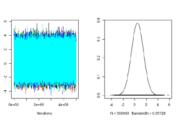
Government office region: South East



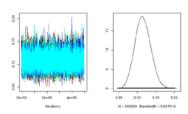
Government office region: South West



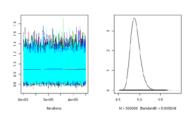
Government office region: Wales



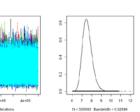
Government office region: Scotland



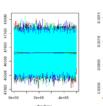
Government office region: Northern Ireland

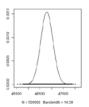


Residential area: Rural



Area-level Random Effect





Interviewer-level Random **Effect**

Household-level Random Effect

DIC

B.6.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Fixed Effect		
Intercept 1	95,658	(1,994,382; 3,011,312)
Intercept 2	94,764	(2,502,414; 2,835,027)
Intercept 3	93,782	(2,443,360; 3,293,906)
Age (16-30)		
31-45	168,099	(92,200; 91,782)
46-60	168,154	(104,937; 112,080)
61-75	183,204	(165,764; 149,864)
76 or above	163,132	(129,298; 131,586)
Marital status (Currently married/ cohabitation)		
Currently not married	150,495	(143,100; 111,625)
Missing	206,771	(20,520; 20,676)
Employment status (Employed)		
Self-employed	199,961	(28,476; 24,095)
Unemployed	189,670	(43,406; 37,872)
Retired	175,963	(110,469; 96,180)
Full-time Student	207,169	(56,322; 62,132)
Other Employment Status	202,034	(46,585; 41,720)
Missing	115,764	(27,090; 21,500)
Highest education level (Degree)		
Other Higher Degree	198,271	(36,552; 41,157)
A-level or Equivalent	196,401	(53,484; 56,355)
GCSE or Equivalent	192,923	(62,188; 65,940)
Other Qualification	195,687	(47,256; 42,516)
No Qualification	185,658	(51,984; 58,464)
Missing	209,275	(33,320; 33,068)
Ethnicity (White)		
Mixed	182,084	(27,798; 27,762)
Asian	114,561	(56,862; 53,141)
Black	130,450	(53,244; 46,387)
Other Ethnic Group	141,679	(20,760; 23,650)
Missing	216,876	(40,950; 41,175)
Born in the UK (Yes)		
No	178,236	(34,736; 32,522)
Missing	215,515	(34,167; 41,679)
Individual monthly income		
Log transformed income	225,906	(2,012,985; 1,662,430)
Quadratic term of log transformed income	219,096	(1,710,648; 1,249,185)

ariable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Belong to a religion (Yes)		
No	168,135	(41,373; 38,792)
Missing	228,697	(17,364; 26,230)
Level of interest in politics (Very interest)		
Fairly	201,370	(99,144; 119,448)
Not very	193,708	(109,204; 105,138)
Not at all interested	187,887	(111,918; 103,891)
Missing	125,643	(23,695; 23,785)
Supported party (Conservative)		
Labour	151,613	(66,304; 71,936)
Liberal Democrat	172,550	(35,152; 42,060)
Scottish National Party	160,761	(33,520; 29,016)
Plaid Cymru	171,615	(23,675; 23,520)
Green Party	177,495	(34,824; 31,339)
Ulster Unionist	158,595	(46,772; 37,024)
SDLP	170,221	(35,208; 38,619)
Alliance Party	155,629	(32,011; 28,830)
Democratic Unionist	150,738	(42,192; 37,448)
Sinn Fein	141,036	(35,360; 30,666)
Other party	169,956	(69,450; 63,336)
Cannot vote	206,351	(31,339; 29,154)
None	169,574	(38,322; 31,535)
Missing	177,711	(41,643; 40,383)
Voluntary work in the last 12 months (Yes)		
No	183,400	(65,076; 75,712)
Donation to charity in the last 12 months (Yes)		
No	183,287	(28,956; 32,648)
Missing	198,023	(20,012; 20,656)
Environmental Concern Score	177,392	(196,896; 203,970)
Believe green is an alternative living style (Agree))	
Disagree	207,322	(39,136; 42,880)
Missing	174,203	(20,384; 18,357)
Ownership of car(s) (Yes)		
No	82,043	(43,596; 43,660)
Missing	91,688	(24,395; 24,865)
Pensioner(s) in household (Yes)		
No	116,837	(175,344; 150,888)
Children aged 0-2 in household (Yes)		
No	88,005	(250,800; 212,889)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Children aged 3-4 in household (Yes)		
No	91,783	(201,159; 193,254)
Children aged 5-11 in household (Yes)		
No	84,585	(136,944; 142,844)
Children aged 12-15 in household (Yes)		
No	82,909	(196,581; 183,480)
Household structure (Single household without children)		
Single household with children	109,299	(109,000; 80,472)
Non-single household without children	127,311	(190,410; 193,428)
Non-single household with children	98,972	(317,616; 290,466)
Tenure type (Home owned outright)		
Home owned with mortgage	91,238	(73,619; 79,760)
Home social rent	94,532	(51,062; 60,333)
Home private/ employer rented	97,049	(70,575; 70,368)
Other	121,550	(26,952; 20,340)
Missing	90,739	(24,905; 27,522)
Dwelling type (Detached house)		
Semi-detached house/ bungalow	85,203	(70,624; 67,815)
End terraced/ terraced house/ bungalow	86,851	(66,534; 71,100)
Flat/ maisonette	93,918	(72,784; 64,134)
Others	112,694	(26,496; 24,065)
Missing	104,138	(199,830; 188,384)
Trash, junk and rubbish on the street in the neighbourhood (Yes)		
No	83,537	(509,523; 364,673)
Missing	103,417	(235,360; 211,392)
Sample composition (GPS)		
Former BHPS	623,418	(44,028; 44,220)
EMBS	868,329	(50,590; 48,222)

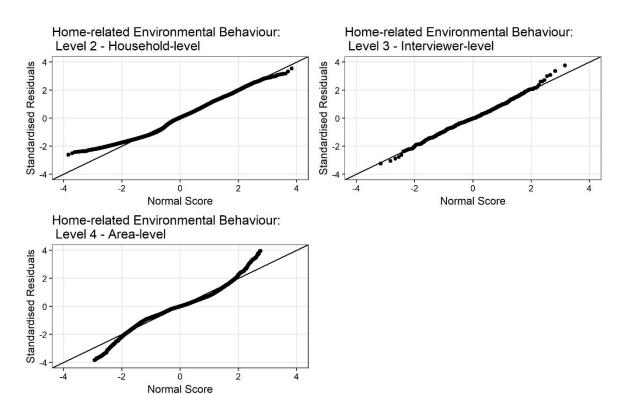
Appendix B

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Government office region (North East)		
North West	97,731	(548,328; 757,302)
Yorkshire and the Humber	92,417	(531,570; 725,685)
East Midlands	93,204	(485,025; 460,575)
West Midlands	85,944	(577,809; 581,438)
East of England	102,035	(682,007; 715,300)
London	111,475	(591,852; 624,240)
South East	96,336	(840,492; 678,240)
South West	73,007	(319,858; 472,894)
Wales	89,409	(433,920; 527,260)
Scotland	75,654	(542,184; 440,370)
Northern Ireland	97,508	(404,250; 356,475)
Residential Area (Urban)		
Rural	692,459	(42,687; 38,936)
Random Effect		
Area	932	(920,968; 416,520)
Interviewer	38,004	(42,000; 34,488)
Household	164,307	(519,436; 352,768)
DIC	103,711	(274,593; 281,164)

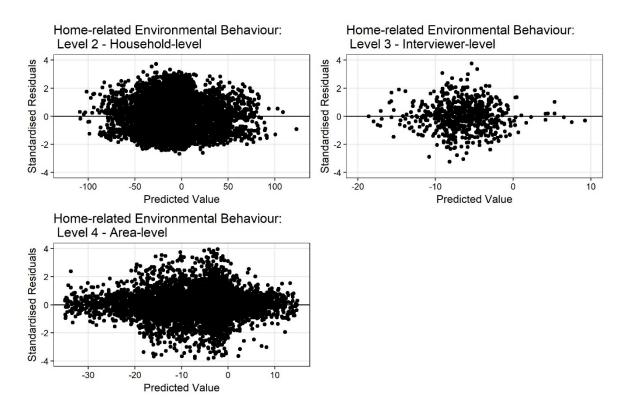
^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

B.7 Home-related Environmental Behaviour: Model Validations and Diagnostics

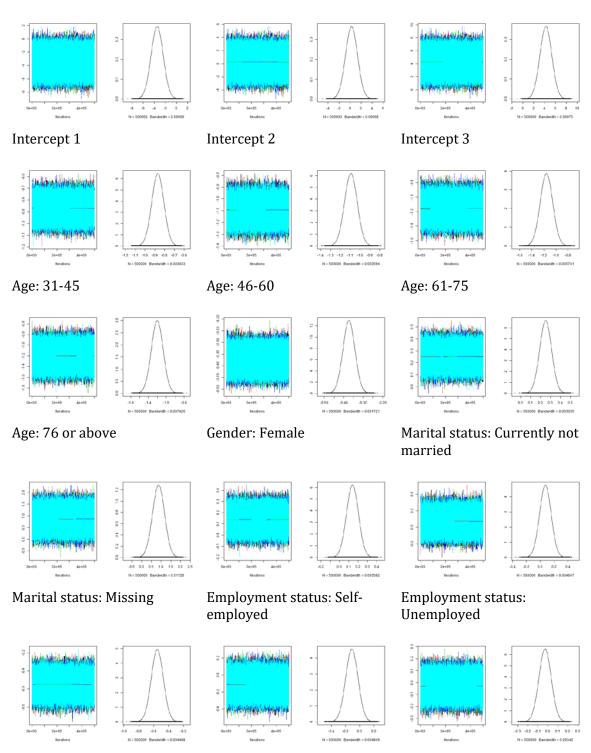
B.7.1 Normal Plots for Household-, Interviewer- and Area-levels



B.7.2 Plot of Standardised Residuals against Fitted Values

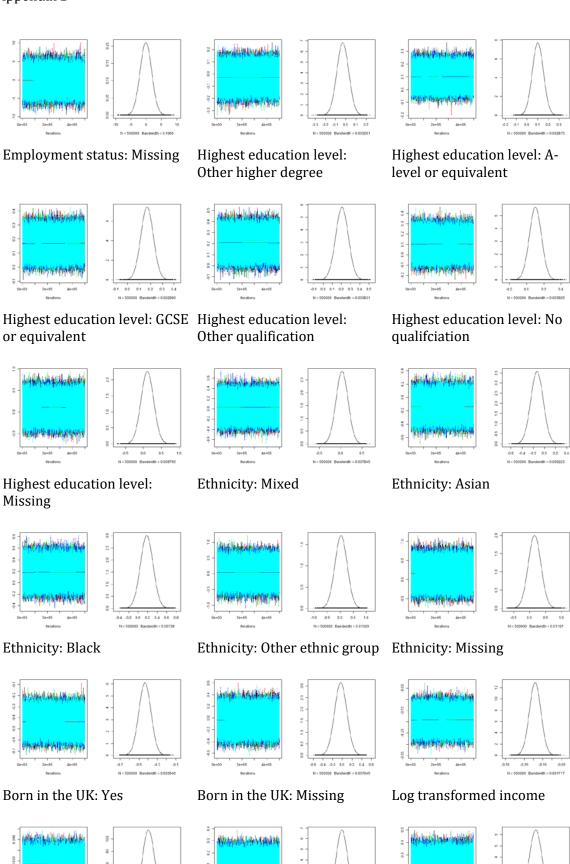


B.7.3 Trace Plots of the Estimates and the Kernel Density Plots of the Posterior Distribution



Employment status: Retired

Employment status: Full-time Employment status: Other student

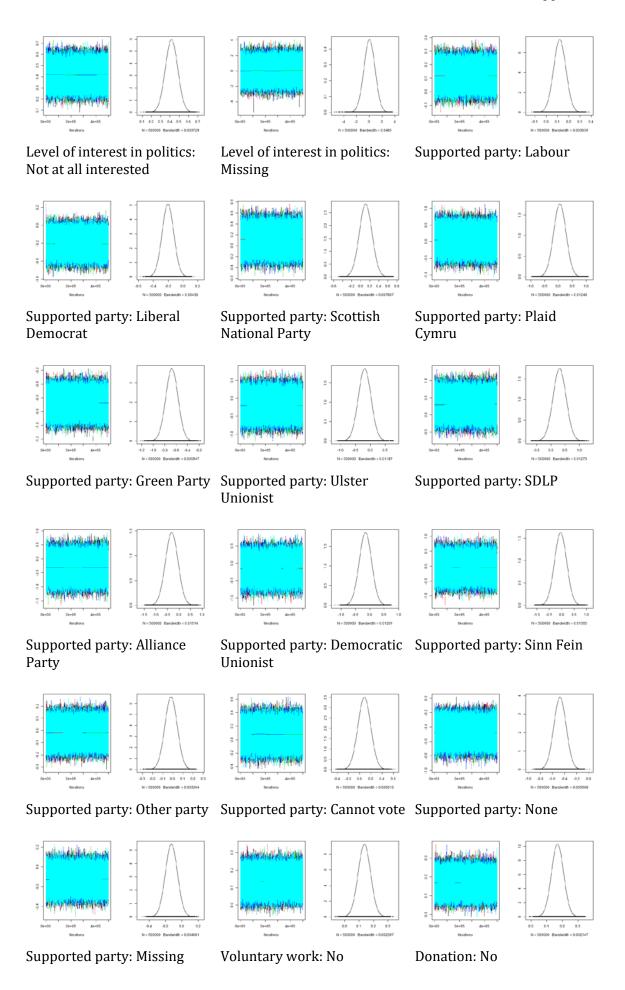


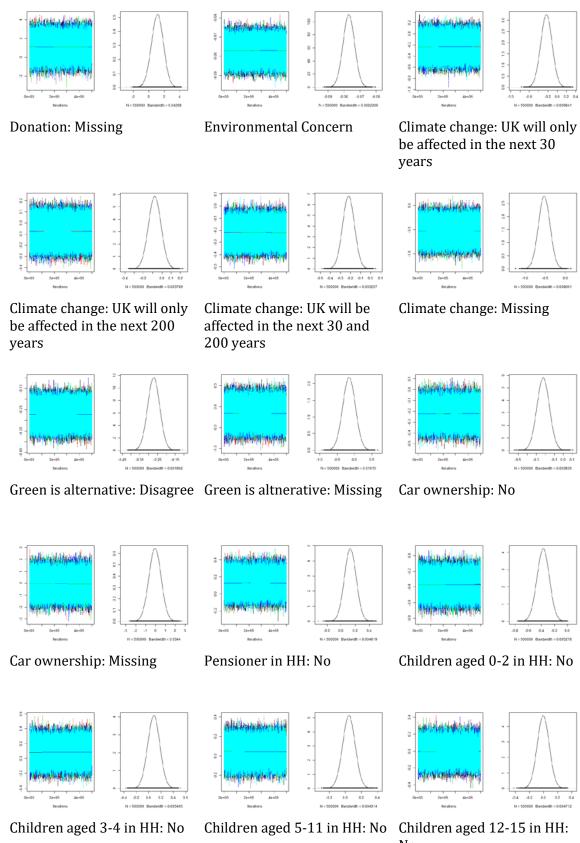
Quadratic term of log transformed income

0 20 20 10 00 01 02 03 0

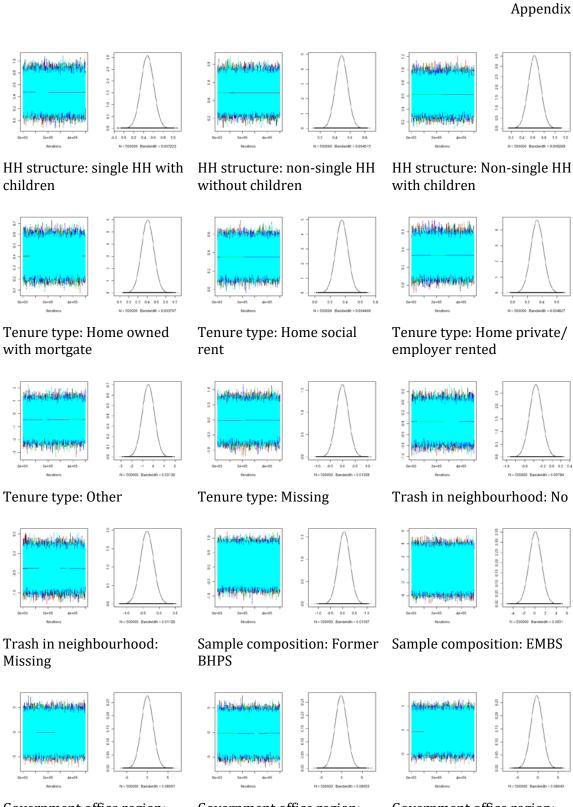
Level of interest in politics: Faily

Level of interest in politics: Not very





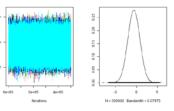
No



Government office region: North West

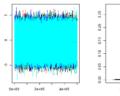
Government office region: West Midlands

Government office region: Yorkshire and the Humber



Government office region: East of England

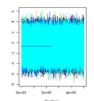
Government office region: East Midlands



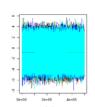


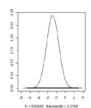
Government office region: London

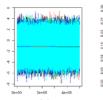
Appendix B

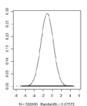




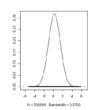




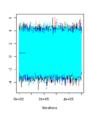


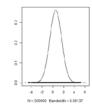


Government office region: South East

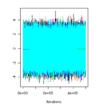


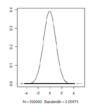
Government office region: South West



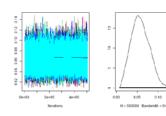


Government office region: Wales

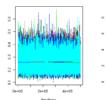




Government office region: Scotland

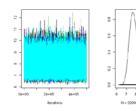


Government office region: Northern Ireland





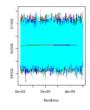
Residential area: Rural

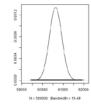


Area-level Random Effect

Interviewer-level Random Effect

Household-level Random Effect





DIC

B.7.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Fixed Effect		
Intercept 1	246,437	(2,749,790; 1,789,676)
Intercept 2	246,669	(2,139,916; 2,057,780)
Intercept 3	244,978	(2,645,025; 2,123,100)
Age (16-30)		
31-45	166,486	(82,263; 96,420)
46-60	166,498	(156,600; 114,875)
61-75	188,993	(185,096; 191,022)
76 or above	169,840	(179,820; 170,975)
Gender (Male)		
Female	262,650	(58,800; 53,604)
Marital status (Currently married/cohabitation)		
Currently not married	152,804	(146,073; 153,986)
Missing	212,858	(24,100; 23,680)
Employment status (Employed)		
Self-employed	196,879	(27,798; 33,752)
Unemployed	196,000	(66,576; 45,230)
Retired	179,159	(99,522; 87,006)
Full-time Student	217,667	(80,223; 82,004)
Other Employment Status	199,411	(45,199; 42,690)
Missing	237,788	(23,975; 27,198)
Highest education level (Degree)		
Other Higher Degree	203,829	(53,796; 42,720)
A-level or Equivalent	189,954	(63,924; 66,435)
GCSE or Equivalent	188,595	(71,295; 70,290)
Other Qualification	190,744	(68,832; 66,255)
No Qualification	184,408	(57,304; 65,610)
Missing	216,348	(41,040; 36,368)
Ethnicity (White)		
Mixed	178,845	(29,370; 30,562)
Asian	108,468	(61,460; 56,953)
Black	128,215	(45,459; 66,645)
Other Ethnic Group	143,543	(25,760; 28,452)
Missing	229,113	(47,630; 47,320)
Born in the UK (Yes)		
No	176,414	(38,408; 37,784)
Missing	212,274	(37,776; 42,741)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Individual monthly income		
Log transformed income	230,221	(1,361,147; 1,351,280)
Quadratic term of log transformed income	221,877	(1,428,200; 1,125,845)
Level of interest in politics (Very interest)		
Fairly	200,908	(124,675; 122,075)
Not very	191,118	(120,850; 151,960)
Not at all interested	189,541	(140,244; 134,125)
Missing	122,811	(25,870; 28,536)
Supported party (Conservative)		
Labour	148,315	(81,141; 66,287)
Liberal Democrat	174,846	(36,144; 36,064)
Scottish National Party	153,579	(36,296; 37,168)
Plaid Cymru	174,231	(27,918; 29,748)
Green Party	186,773	(37,665; 37,701)
Ulster Unionist	135,821	(51,887; 57,785)
SDLP	141,354	(52,260; 43,960)
Alliance Party	149,612	(36,192; 39,186)
Democratic Unionist	136,909	(56,446; 55,406)
Sinn Fein	131,721	(46,150; 47,040)
Other party	165,441	(71,925; 73,321)
Cannot vote	212,917	(39,483; 40,338)
None	171,087	(32,746; 35,144)
Missing	174,077	(56,823; 48,477)
Voluntary work in the last 12 months (Yes)		
No	187,993	(81,060; 90,848)
Donation to charity in the last 12 months (Yes)		
No	178,366	(33,026; 43,190)
Missing	218,188	(20,656; 23,130)
Environmental Concern Score	178,133	(221,880; 271,584)
Believe in the effect of climate change in the UK (U) will not be affected in the next 30 and 200 years)	JK	
UK will only be affected in the next 30 years	211,598	(41,240; 39,294)
UK will only be affected in the next 200 years	207,549	(109,008; 115,479)
UK will be affected in the next 30 and 200 years	199,157	(137,839; 139,400)
Missing	181,530	(42,920; 39,186)
Believe green is an alternative living style (Agree)		
Disagree	208,249	(39,368; 42,453)
Missing	162,648	(20,868; 23,750)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Ownership of car(s) (Yes)		
No	96,175	(42,075; 44,980)
Missing	90,128	(30,018; 36,112)
Pensioner(s) in household (Yes)		
No	108,849	(192,444; 173,160)
Children aged 0-2 in household (Yes)		
No	78,783	(303,150; 269,724)
Children aged 3-4 in household (Yes)		
No	81,488	(250,184; 289,432)
Children aged 5-11 in household (Yes)		
No	76,423	(173,016; 154,380)
Children aged 12-15 in household (Yes)		
No	73,738	(196,622; 228,033)
Household structure (Single household without children)		
Single household with children	100,442	(91,828; 109,128)
Non-single household without children	121,588	(152,861; 186,681)
Non-single household with children	89,492	(312,276; 338,372)
Tenure type (Home owned outright)		
Home owned with mortgage	81,927	(86,275; 103,320)
Home social rent	90,606	(59,631; 72,030)
Home private/ employer rented	89,571	(77,024; 73,728)
Other	113,883	(32,200; 28,518)
Missing	83,839	(30,924; 39,321)
Trash, junk and rubbish on the street in the neighbourhood (Yes)		
No	81,377	(477,398; 469,820)
Missing	88,748	(161,024; 202,312)
Sample composition (GPS)		
Former BHPS	877,734	(46,314; 49,040)
EMBS	978,015	(65,702; 66,937)

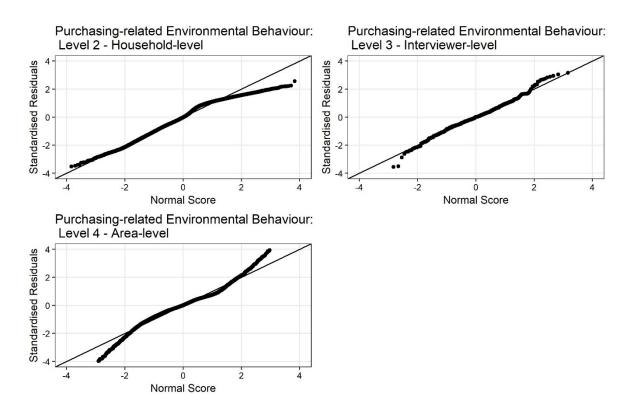
Appendix B

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Government office region (North East)		
North West	304,430	(393,762; 480,150)
Yorkshire and the Humber	283,010	(321,216; 387,576)
East Midlands	275,815	(332,520; 395,733)
West Midlands	268,901	(409,738; 392,564)
East of England	306,145	(385,344; 358,900)
London	331,841	(402,449; 458,320)
South East	283,011	(511,602; 424,833)
South West	236,231	(323,680; 358,144)
Wales	269,419	(318,976; 327,686)
Scotland	251,351	(373,388; 366,405)
Northern Ireland	310,332	(243,276; 262,986)
Residential Area (Urban)		
Rural	928,670	(49,700; 45,918)
Random Effect		
Area	561	(2,915,976; 959,502)
Interviewer	31,578	(102,942; 89,984)
Household	189,571	(182,004; 191,870)
DIC	104,501	(157,509; 142,800)

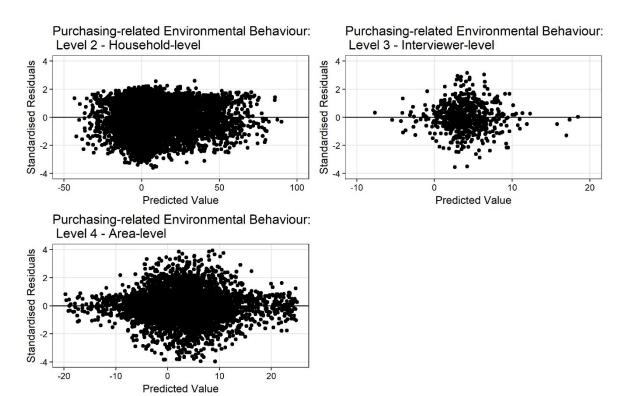
^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

B.8 Purchasing-related Environmental Behaviour: Model Validations and Diagnostics

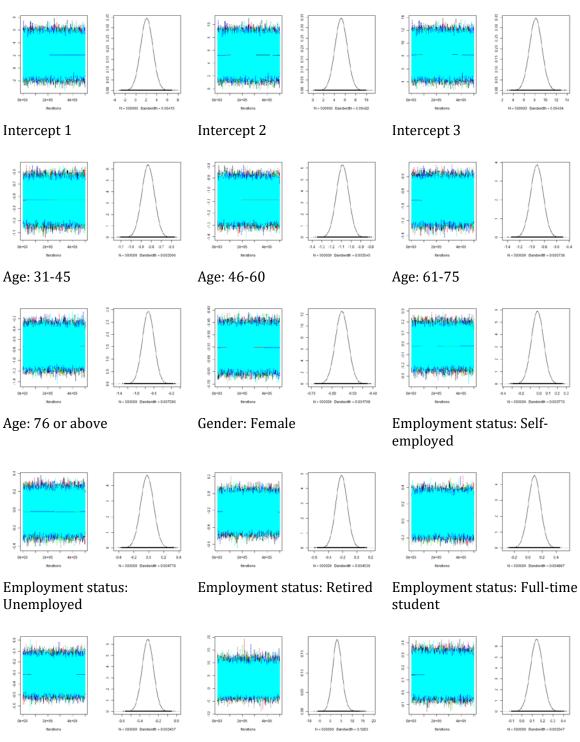
B.8.1 Normal Plots for Household-, Interviewer- and Area-levels



B.8.2 Plot of Standardised Residuals against Fitted Values



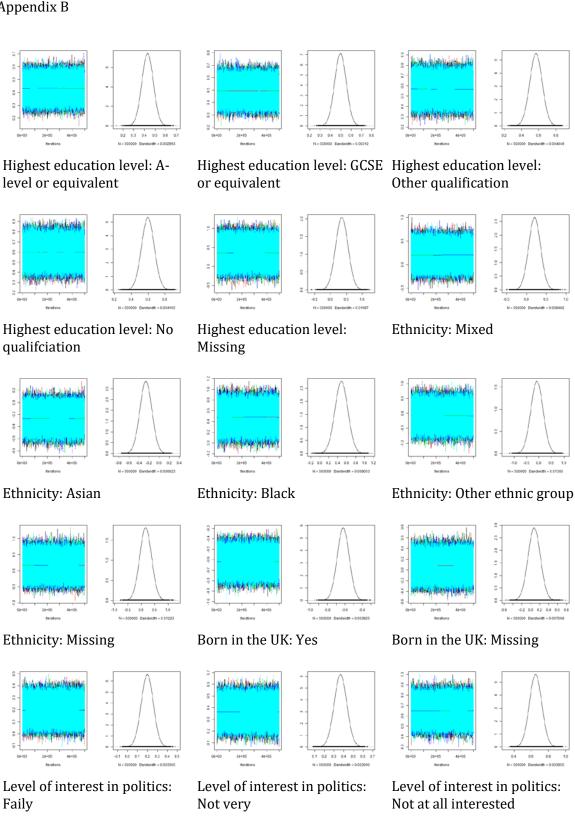
B.8.3 Trace Plots of the Estimates and the Kernel Density Plots of the Posterior Distribution



Employment status: Other

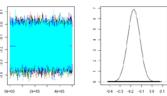
Employment status: Missing

Highest education level: Other higher degree



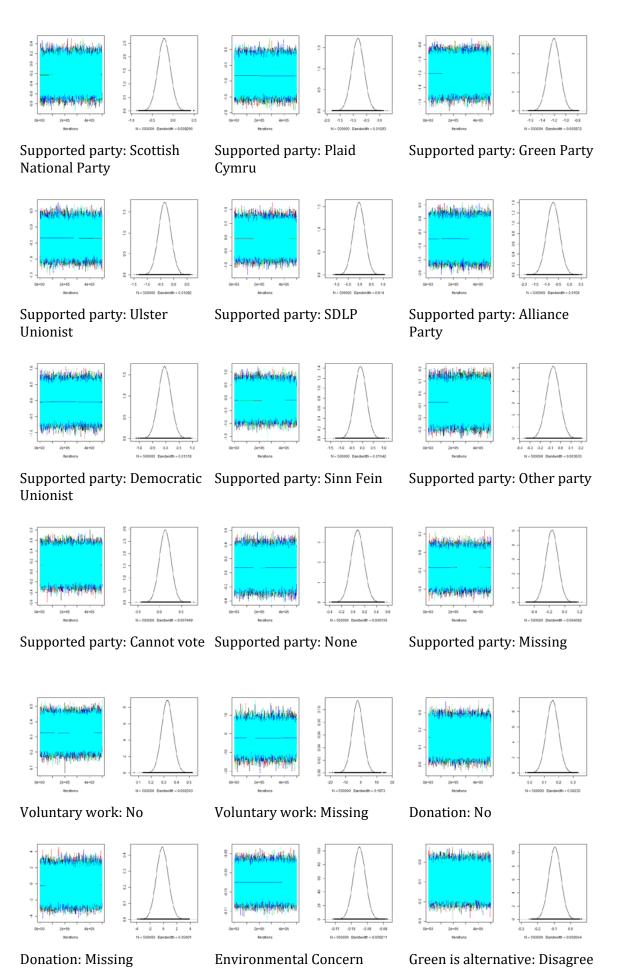
Level of interest in politics:

Level of interest in politics: Missing

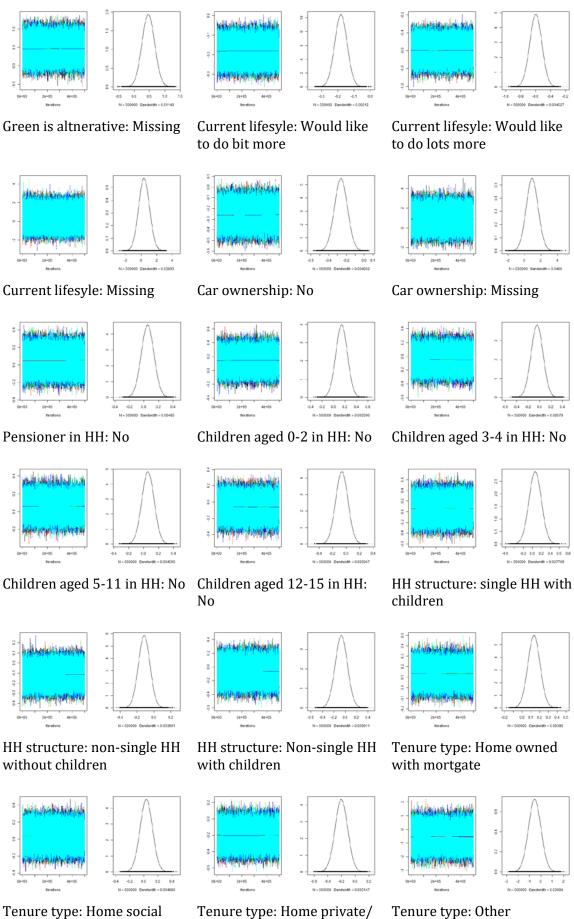


Supported party: Labour

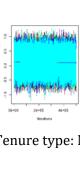
Supported party: Liberal Democrat

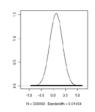


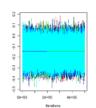
rent

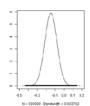


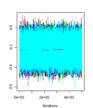
employer rented

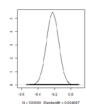








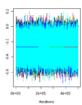


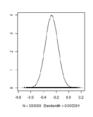


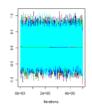
Tenure type: Missing

house/bungalow

Dwelling type: Semi-detached Dwelling type: End terraced/ terraced house/bungalow









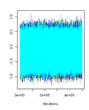


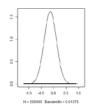


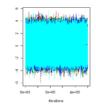
Dwelling type: Flat/ Maisonette

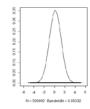
Dwelling type: Others

Dwelling type: Missing

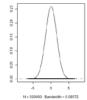








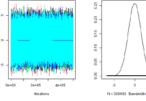


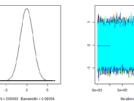


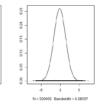
Sample composition: Former **BHPS**

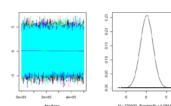
Sample composition: EMBS

Government office region: North West





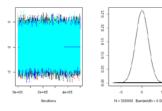




Government office region: Yorkshire and the Humber

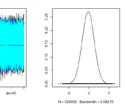
Government office region: East Midlands

Government office region: West Midlands









Government office region: East of England

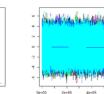
Government office region: London

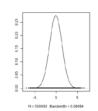
Government office region: South East

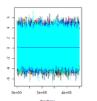
Appendix B

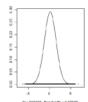






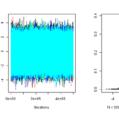






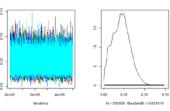
Government office region: South West

Government office region: Wales



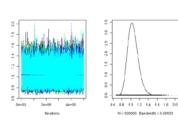
20 -

Government office region: Scotland

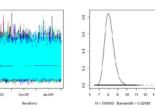


Area-level Random Effect

Government office region: Northern Ireland



Residential area: Rural



Interviewer-level Random Effect

Household-level Random Effect

DIC

B.8.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Fixed Effect		
Intercept 1	74,027	(2,638,905; 3,600,030)
Intercept 2	73,807	(2,461,547; 2,692,400)
Intercept 3	73,649	(2,515,227; 2,167,888)
Age (16-30)		
31-45	162,497	(98,952; 85,248)
46-60	175,343	(114,241; 107,016)
61-75	184,500	(182,325; 165,930)
76 or above	161,034	(132,888; 151,800)
Gender (Male)		
Female	250,723	(40,296; 40,296)
Marital status (Currently married/ cohabitation)		
Currently not married	184,995	(27,762; 24,765)
Missing	190,228	(27,576; 24,780)
Employment status (Employed)	166,204	(104,100; 98,651)
Self-employed	221,122	(48,609; 51,852)
Unemployed	185,659	(32,130; 28,704)
Retired	226,274	(19,964; 19,074)
Full-time Student		
Other Employment Status	186,028	(44,850; 48,246)
Missing	186,468	(65,175; 59,248)
Highest education level (Degree)	179,686	(63,518; 55,452)
Other Higher Degree	180,040	(48,136; 55,939)
A-level or Equivalent	171,310	(53,713; 49,330)
GCSE or Equivalent	211,590	(28,254; 29,754)
Other Qualification		
No Qualification	172,803	(33,824; 30,982)
Missing	102,763	(62,101; 60,684)
Ethnicity (White)	117,667	(49,544; 44,370)
Mixed	141,516	(28,386; 28,692)
Asian	222,383	(37,784; 34,237)
Black		
Other Ethnic Group	163,524	(37,600; 41,319)
Missing	200,083	(33,432; 37,035)
Level of interest in politics (Very interest)		
Fairly	188,283	(117,120; 123,376)
Not very	180,799	(121,394; 116,820)
Not at all interested	173,865	(101,612; 117,528)
Missing	121,423	(24,955; 27,756)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*		
Supported party (Conservative)				
Labour	140,448	(78,480; 71,625)		
Liberal Democrat	155,369	(43,160; 43,900)		
Scottish National Party	147,947	(30,864; 33,285)		
Plaid Cymru	147,831	(29,652; 29,680)		
Green Party	165,243	(35,600; 31,577)		
Ulster Unionist	129,354	(56,654; 58,175)		
SDLP	128,488	(61,404; 44,710)		
Alliance Party	129,534	(44,490; 36,536)		
Democratic Unionist	125,870	(54,704; 53,484)		
Sinn Fein	118,316	(50,996; 43,101)		
Other party	159,011	(72,420; 77,265)		
Cannot vote	214,942	(33,180; 31,542)		
None	163,258	(32,487; 32,263)		
Missing	161,389	(46,541; 48,168)		
Voluntary work in the last 12 months (Yes)				
No	170,974	(66,176; 71,318)		
Missing	105,678	(24,425; 27,708)		
Donation to charity in the last 12 months (Yes)				
No	167,920	(28,235; 29,778)		
Missing	173,808	(23,910; 23,430)		
Environmental Concern Score	163,056	(229,482; 248,706)		
Believe green is an alternative living style (Agree	e)			
Disagree	192,307	(41,176; 48,380)		
Missing	155,443	(24,905; 21,020)		
Thoughts about current lifestyle and the enviror (I'm happy with what I do at the moment)	nment			
Would like to do bit more	193,381	(34,125; 32,732)		
Would like to do lots more	191,173	(27,378; 24,050)		
Missing	216,029	(21,224; 21,136)		
Ownership of car(s) (Yes)				
No	93,492	(42,579; 39,080)		
Missing	96,820	(28,356; 25,525)		
Pensioner(s) in household (Yes)		·		
No	104,455	(199,864; 213,009)		
Children aged 0-2 in household (Yes)				
No	79,145	(259,063; 290,650)		
Children aged 3-4 in household (Yes)	·			

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Children aged 5-11 in household (Yes)		
No	74,557	(175,410; 198,016)
Children aged 12-15 in household (Yes)		
No	74,846	(219,298; 222,640)
Household structure (Single household without children)		
Single household with children	98,047	(113,178; 109,944)
Non-single household without children	104,682	(116,242; 97,206)
Non-single household with children	80,864	(256,996; 327,040)
Tenure type (Home owned outright)		
Home owned with mortgage	80,866	(83,266; 100,880)
Home social rent	88,534	(67,032; 65,814)
Home private/ employer rented	85,544	(64,890; 69,808)
Other	97,412	(25,305; 28,338)
Missing	80,652	(32,508; 35,936)
Dwelling type (Detached house)		
Semi-detached house/bungalow	77,328	(74,625; 70,826)
End terraced/ terraced house/ bungalow	78,795	(87,732; 81,648)
Flat/ maisonette	84,800	(80,946; 78,432)
Others	96,316	(31,297; 28,308)
Missing	89,264	(36,080; 44,250)
Sample composition (GPS)		
Former BHPS	707,652	(50,080; 49,740)
EMBS	852,223	(55,032; 63,973)
Government office region (North East)		
North West	77,528	(610,700; 446,789)
Yorkshire and the Humber	74,995	(522,340; 399,819)
East Midlands	74,720	(454,640; 412,251)
West Midlands	69,295	(432,498; 489,332)
East of England	84,002	(594,630; 596,064)
London	88,594	(613,225; 540,290)
South East	76,696	(935,527; 617,306)
South West	56,193	(481,806; 458,804)
Wales	68,703	(546,570; 455,455)
Scotland	56,342	(559,300; 488,349)
Northern Ireland	75,628	(489,345; 404,800)
Residential Area (Urban)		
Rural	787,395	(55,344; 44,154)

Appendix B

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Random Effect		
Area	541	(6,889,324; 1,288,162)
Interviewer	37,333	(38,142; 29,610)
Household	169,354	(260,910; 248,788)
DIC	103,089	(190,365; 246,882)

^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

Appendix C

C.1 Summary of Sampling Method and Mode of Data Collection

	Fieldwoi	rk Period	Sampling Method	Mode of Data Collection
	Start Date	End Date		
Argentina	07/10/2010	10/20/2010	Stratified three-stage probability sampling	Face-to-face interviews (PAPI)
Australia	05/01/2012	08/08/2012	One-stage probability sampling	Self-completion questionnaire
Austria	07/21/2010	09/05/2010	Stratified three-stage probability sampling	Face-to-face interviews (CAPI)
Belgium	03/17/2010	07/28/2010	Stratified two-stage probability sampling	Self-completion for ISSP module, CAPI for background variables
Bulgaria	08/16/2011	09/20/2011	Three-stage random probability sampling	Face-to-face interviews (PAPI)
Canada	01/15/2011	04/15/2011	Stratified two-stage probability sampling	Self-completion questionnaire
Chile	11/20/2010	12/16/2010	Stratified three-stage probability sampling	Face-to-face interviews (PAPI)
Croatia	05/20/2011	06/20/2011	Stratified three-stage probability sampling	Face-to-face interviews (PAPI)
Czech Republic	06/01/2010	06/30/2010	Stratified three-stage probability sampling	Face-to-face interviews (PAPI)
Denmark	10/21/2010	04/05/2011	One-stage probability sampling	Self-completion - combined mail survey and web survey
Finland	10/22/2010	01/10/2011	Stratified one-stage probability sampling	Self-completion, CASI
France	09/01/2010	12/31/2010	Two-stage probability sampling	Self-completion questionnaire
Germany	05/31/2010	10/30/2010	Stratified two-stage probability sampling	CASI for ISSP module, CAPI for background variables
Iceland	03/21/2012	11/28/2012	One-stage probability sampling	Self-completion - combined mail survey and web survey
Israel	03/29/2011	08/15/2011	Stratified 4+stage probability sampling	Face-to-face interviews (PAPI)
Japan	11/27/2010	12/05/2010	Stratified two-stage probability sampling	Self-completion questionnaire
Republic of Korea	06/28/2010	08/31/2010	Three-stage probability sampling	Face-to-face interviews (PAPI)

	Fieldwoi	rk Period	Sampling Method	Mode of Data Collection
	Start Date	End Date		
Latvia	07/28/2011	08/15/2011	Stratified three-stage probability sampling	Face-to-face interviews (PAPI)
Lithuania	11/30/2010	02/03/2011	Clustered two-stage probability sampling	Face-to-face interviews (PAPI)
Mexico	08/17/2011	09/18/2011	Stratified three-stage probability sampling	Face-to-face interviews (PAPI)
Netherlands	03/08/2011	12/01/2011	Two-stage probability sampling	Self-completion questionnaire
New Zealand	08/19/2010	11/30/2010	Stratified two-stage probability sampling	Self-completion questionnaire
Norway	03/09/2011	05/11/2011	One-stage probability sampling	Self-completion – combined mail survey and web survey
Philippines	09/24/2010	09/27/2010	Stratified 4+ stage probability sampling	Face-to-face interviews (PAPI)
Portugal	11/03/2012	03/04/2013	Stratified three-stage probability sampling	Face-to-face interviews (CAPI)
Russian Federation	12/01/2010	12/21/2010	Stratified 4+ stage probability sampling	Face-to-face interviews (PAPI)
Slovakia	09/21/2009	10/22/2009	Two-stage probability sampling	Face-to-face interviews (PAPI)
Slovenia	03/09/2011	06/15/2011	Stratified two-stage probability sampling	Face-to-face interviews (PAPI)
South Africa	11/01/2010	12/10/2010	Stratified two-stage probability sampling	Face-to-face interviews (PAPI)
Spain	05/04/2010	07/10/2010	Stratified two-stage probability sampling	Face-to-face interviews (PAPI)
Sweden	02/16/2010	05/05/2010	One-stage probability sampling	Self-completion questionnaire
Switzerland	03/07/2011	09/26/2011	Stratified one-stage probability sampling	Face-to-face interviews (CAPI)
Taiwan	07/11/2010	09/23/2010	Stratified three-stage probability sampling	Face-to-face interviews (PAPI or CAPI)
Turkey	10/01/2010	11/30/2010	Stratified three-stage probability sampling	Face-to-face interviews (PAPI or CAPI)
United Kingdom	06/11/2010	11/13/2010	Stratified three-stage probability sampling	Self-completion for ISSP module, face-to-face for background variables
United States	03/18/2010	08/14/2010	Stratified 4+ stage probability sampling	Face-to-face with CAPI + CAPI, phone

C.2 Summary of Response Rate and Language used in Interviews

			Details about Is	ssued Sample			Language(s)
	Staring Address	Successful Interview	Unsuccessful Interview	Unknown Eligibility	Ineligible	Response Rate ²	
Argentina	4,632	1,130	2,686	18	798	29.6%	Spanish
Australia	6,250	1,946	903	3396	5	68.3%	English
Austria	1,736	1,019	626	0	91	61.9%	German
Belgium	2,365	1,142	1,136	24	63	50.1%	Dutch
Bulgaria	2,275	1,003	1,012	0	260	49.8%	Bulgarian
Canada	5,000	985	3,643	0	372	21.3%	English, French
Chile	1,800	1,436	364	0	0	79.8%	Spanish
Croatia	2,576	1,210	1,343	0	23	47.4%	Croatian
Czech Republic	2,200	1,428	691	44	37	67.4%	Czech
Denmark	2,500	1,297	1,203	0	0	51.9%	Danish
Finland	2,500	1,211	1,282	0	7	48.6%	Finnish, Swedish
France	10,000	2,339	7,376	0	285	24.1%	French
Germany	4,564	1,407	2,643	73	441	34.7%	German
Iceland	1,500	798	692	0	10	53.6%	Icelandic
Israel	1,669	1,023	581	0	65	63.8%	Hebrew, Arabic, Russian
Japan	1,800	1,307	416	26	51	75.9%	Japanese
Republic of Korea	2,500	1,576	763	0	161	67.4%	Korean

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 $^{^{2} \} Response \ Rate = \frac{Successful \ Interview}{Starting \ Address- \ Unknown \ Eligibility - Ineligible}$

			Details about Is	ssued Sample			Language(s)
	Staring Address	Successful Interview	Unsuccessful Interview	Unknown Eligibility	Ineligible	Response Rate ²	
Latvia	2,034	1,000	453	454	127	68.8%	Latvian, Russian
Lithuania	3,805	1,023	1,791	0	991	36.4%	Lithuanian
Mexico	2,168	1,741	427	0	0	80.3%	Spanish
Netherlands	4,500	1,472	2,903	125	0	33.6%	Dutch
New Zealand	2,520	1,172	1,250	0	98	48.4%	English
Norway	3,600	1,382	111	2,105	2	92.6%	Norwegian
Philippines	2,831	1,200	1,470	50	111	44.9%	English, Ilocano, Cebuano, Hiligaynon, Maranao, Bicol, Waray
Portugal	2,256	1,022	1,042	0	192	49.5%	Portuguese
Russian Federation	3,408	1,619	1,681	0	108	49.1%	Russian
Slovakia	1,925	1,165	635	0	125	64.7%	Slovak, Hungarian
Slovenia	1,800	1,082	561	29	128	65.9%	Slovenian
South Africa	3,500	3,112	340	0	48	90.2%	English, Afrikaans, Tsonga, Tswana, Xhosa, Zulu
Spain	4,000	2,560	1,034	0	406	71.2%	Spanish
Sweden	2,001	1,181	798	0	22	59.7%	Swedish
Switzerland	2,409	1,176	785	403	45	60.0%	German, French, Italian
Taiwan	4,602	2,209	2,199	0	194	50.1%	Mandarin Chinese, Fukien dialect, Hakka dialect
Turkey	3,400	1,665	1,235	0	500	57.4%	Turkish
United Kingdom	2,260	1,120	898	17	225	55.5%	English
United States	4,136	2,044	621	0	1,471	76.7%	English, Spanish

C.3 Descriptive Statistics of the Final Analysis Sample Dataset (N = 45,765) - Categorical Variables

	N	%
Gender		
Female	24,891	54.4
Male	20,874	45.6
Age		
15-30	8,897	19.4
31-45	11,841	25.9
46-60	12,380	27.1
61-75	9,703	21.2
76+	2,944	6.4
Employment Status		
Employed	24,216	52.9
Unemployed	3,167	6.9
Student	2,647	5.8
Retired	10,027	21.9
Homemaker	3,311	7.2
Other	2,397	5.2
Highest Education		
No formal qualification	3,149	6.9
Lowest qualification	5,976	13.1
Intermediate secondary completed	9,966	21.8
Higher secondary completed	11,598	25.3
University degree uncompleted	6,630	14.5
University degree completed	8,446	18.5
Marital Status		
Currently married	24,743	54.1
Currently not married	9,565	20.9
Never married	11,457	25.0
Household Size		
1-person	7,571	16.5
2-person	14,571	31.8
3-person	8,607	18.8
4-person	8,389	18.3
5-person+	6,627	14.5
Area of Residency		
City	13,214	28.9
Small City	17,923	39.2
Rural	14,628	32.0

	N	%
Self-rated Social Status		
10%	1,272	2.8
20%	2,173	4.7
30%	4,522	9.9
40%	6,220	13.6
50%	10,930	23.9
60%	8,277	18.1
70%	5,830	12.7
80%	3,192	7.0
90%	710	1.6
100%	539	1.2
not asked	2,100	4.6
Belong to a Religion		
Yes	35,023	76.5
No	10,742	23.5
Post-Materialistic Values		
Post-materialistic	5,069	11.1
Neither post-materialistic nor materialistic	26,730	58.4
Materialistic	13,966	30.5
Voting in the Last Election		
Yes	33,905	74.1
No	8,804	19.2
Not eligible to vote	3,056	6.7
Political Orientation		
Left	11,421	25.0
Centre	8,469	18.5
Right	10,179	22.2
No party affiliation	13,475	29.4
Other	1,005	2.2
not asked	1,216	2.7
Mode of Data Collection		
Face-to-Face Interview (PAPI)	23,391	51.1
Face-to-Face Interview (CAPI)	4,831	10.6
Self-completed questionnaire (interviewer)	3,377	7.4
Self-completed questionnaire (mailed)	11,452	25.0
Self-completed questionnaire (CASI)	1,870	4.1
Self-completed questionnaire (web)	697	1.5
Phone Interview	147	0.3
Total	45,765	100.0

C.4 Descriptive Statistics of the Final Analysis Sample Dataset (N = 45,765) - Continuous Variables

	Mean	SD	Max	Min
Left-Right ideology				
Private enterprise is the best way to solve economic problems	2.18	1.12	0	4
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	1.31	1.15	0	4
Social and Political Trusts				
Social Trust	3.78	2.21	0	8
Political Trust	3.01	1.83	0	8
Environmental Attitudes and Knowledge				
Environmental Risk Perception	19.03	4.79	0	28
Environmental Attitude	14.68	4.98	0	28
Attitudes towards Environment, Science and Economic Growths	7.97	2.86	0	16
Willingness to Make Personal Sacrifice for Environment	4.87	3.16	0	12
Environmental Knowledge	3.80	1.96	0	8
Environmental Justice and Global Cooperation				
For environmental problems, there should be international agreements that countries should be made to follow	0.86	0.84	0	4
Poorer countries should be expected to make less effort than richer countries to protect the environment	2.03	1.2	0	4

C.5 Descriptive Statistics of the Final Analysis Sample Dataset - Categorical Variables (By Countries)

	Argentina	Australia	Austria	Belgium	Bulgaria	Canada	Chile
Gender							
Female	586	1,023	536	595	581	507	857
Male	544	923	483	547	422	478	579
Age							
15-30	261	198	264	202	148	127	318
31-45	320	338	248	288	233	136	403
46-60	279	640	298	316	267	339	390
61-75	192	581	170	250	264	294	229
76+	78	189	39	86	91	89	96
Employment Status							
Employed	644	1,044	591	643	454	436	953
Unemployed	63	44	53	31	82	24	63
Student	49	38	74	78	34	88	52
Retired	140	103	27	64	26	31	249
Homemaker	15	110	27	33	54	52	5
Other	219	607	247	293	353	354	114

	Argentina	Australia	Austria	Belgium	Bulgaria	Canada	Chile
Highest Education							
No formal qualification	122	94	13	25	14	23	314
Lowest qualification	261	317	170	124	58	88	196
Intermediate secondary completed	247	130	490	226	193	397	194
Higher secondary completed	231	215	202	394	236	165	393
University degree uncompleted	204	565	0	229	264	171	236
University degree completed	65	625	144	144	238	141	103
Marital Status							
Currently married	505	1,254	474	675	536	605	641
Currently not married	228	350	213	218	340	234	277
Never married	397	342	332	249	127	146	518
Self-rated Social Status							
10%	30	43	5	8	50	8	81
20%	35	39	7	10	94	14	105
30%	119	74	36	12	238	26	257
40%	202	110	95	41	219	74	305
50%	409	445	145	312	260	154	470
60%	167	464	371	302	93	220	138
70%	117	395	237	306	31	230	51
80%	43	253	107	121	13	185	24
90%	6	77	13	14	4	44	1
100%	2	46	3	16	1	30	4
not asked	0	0	0	0	0	0	0

	Argentina	Australia	Austria	Belgium	Bulgaria	Canada	Chile
Household Size							
1-person	114	268	292	140	210	146	169
2-person	244	853	363	458	334	466	270
3-person	237	314	180	212	209	134	328
4-person	227	317	121	224	170	154	295
5-person+	308	194	63	108	80	85	374
Area of Residency							
City	414	513	241	98	463	268	570
Small City	619	1,026	349	371	180	620	475
Rural	97	407	429	673	360	97	391
Belong to a Religion							
Yes	972	1,346	855	849	927	726	1,251
No	158	600	164	293	76	259	185
Post-Materialistic Values							
Post-materialistic	76	258	143	95	33	168	207
Neither post-materialistic nor materialistic	549	1,245	596	654	508	639	788
Materialistic	505	443	280	393	462	178	441
Voting in the Last Election							
Yes	760	1,898	753	1,022	730	867	972
No	213	34	181	65	246	82	53
Not eligible to vote	157	14	85	55	27	36	411

	Argentina	Australia	Austria	Belgium	Bulgaria	Canada	Chile
Political Orientation							
Left	114	531	377	323	283	316	193
Centre	46	12	0	150	484	293	106
Right	16	608	411	631	196	376	167
No party affiliation	954	795	202	20	15	0	970
Other	0	0	29	18	25	0	0
not asked	0	0	0	0	0	0	0
Mode of Data Collection							
Face-to-Face Interview (PAPI)	1,130	0	0	0	1,003	0	1,436
Face-to-Face Interview (CAPI)	0	0	1,019	0	0	0	0
Self-completed questionnaire (interviewer)	0	0	0	1,142	0	0	0
Self-completed questionnaire (mailed)	0	1,946	0	0	0	985	0
Self-completed questionnaire (CASI)	0	0	0	0	0	0	0
Self-completed questionnaire (web)	0	0	0	0	0	0	0
Phone Interview	0	0	0	0	0	0	0
Total	1,130	1,946	1,019	1,142	1,003	985	1,436

	Croatia	Czech Republic	Denmark	Finland	France	Germany	Israel
Gender							
Female	635	744	685	666	1,032	745	654
Male	575	684	620	545	1,221	662	562
Age							
15-30	286	286	207	279	84	253	319
31-45	335	404	336	256	406	324	321
46-60	316	358	411	374	713	401	273
61-75	230	306	270	301	763	330	220
76+	43	74	81	1	287	99	83
Employment Status							
Employed	600	843	766	650	957	730	695
Unemployed	147	69	49	80	51	83	48
Student	76	90	122	154	31	58	60
Retired	36	4	12	17	51	91	109
Homemaker	30	57	83	51	41	85	103
Other	321	365	273	259	1,122	360	201
Highest Education							
No formal qualification	28	2	74	76	38	28	16
Lowest qualification	144	138	40	91	490	489	103
Intermediate secondary completed	233	607	74	65	535	496	290
Higher secondary completed	553	528	407	380	335	118	220
University degree uncompleted	108	24	512	376	289	77	258
University degree completed	144	129	198	223	566	199	329

	Croatia	Czech Republic	Denmark	Finland	France	Germany	Israel
Marital Status							
Currently married	628	712	718	608	1,403	784	769
Currently not married	236	403	257	140	529	257	163
Never married	346	313	330	463	321	366	284
Self-rated Social Status							
10%	29	34	11	24	70	15	14
20%	84	109	14	33	109	47	23
30%	231	194	44	81	272	66	63
40%	367	284	85	109	457	112	102
50%	499	390	260	230	537	214	249
60%	0	210	284	241	394	464	220
70%	0	134	311	256	263	282	227
80%	0	60	192	197	107	171	164
90%	0	11	36	31	26	27	88
100%	0	2	68	9	18	9	66
not asked	0	0	0	0	0	0	0
Household Size							
1-person	237	330	217	244	541	296	131
2-person	317	461	550	513	1,005	579	292
3-person	283	295	189	181	301	217	207
4-person	271	274	227	175	274	230	215
5-person+	102	68	122	98	132	85	371

	Croatia	Czech Republic	Denmark	Finland	France	Germany	Israel
Area of Residency							
City	392	437	292	109	267	260	621
Small City	372	624	619	733	979	679	272
Rural	446	367	394	369	1,007	468	323
Belong to a Religion							
Yes	1,153	513	1,132	987	1,400	956	1,207
No	57	915	173	224	853	451	9
Post-Materialistic Values							
Post-materialistic	82	99	212	226	363	420	84
Neither post-materialistic nor materialistic	760	792	929	773	1,089	781	726
Materialistic	368	537	164	212	801	206	406
Voting in the Last Election							
Yes	777	939	1,085	877	2,091	1,123	948
No	402	489	77	203	162	284	232
Not eligible to vote	31	0	143	131	0	0	36
Political Orientation							
Left	104	650	550	185	872	684	0
Centre	10	270	106	168	0	86	0
Right	108	475	570	261	800	362	0
No party affiliation	957	0	79	510	581	232	0
Other	31	33	0	87	0	43	0
not asked	0	0	0	0	0	0	1,216

	Croatia	Czech Republic	Denmark	Finland	France	Germany	Israel
Mode of Data Collection							
Face-to-Face Interview (PAPI)	1,210	1,428	0	0	0	0	1,216
Face-to-Face Interview (CAPI)	0	0	0	0	0	295	0
Self-completed questionnaire (interviewer)	0	0	0	0	0	0	0
Self-completed questionnaire (mailed)	0	0	1,083	453	2,253	0	0
Self-completed questionnaire (CASI)	0	0	0	758	0	1,112	0
Self-completed questionnaire (web)	0	0	222	0	0	0	0
Phone Interview	0	0	0	0	0	0	0
Total	1,210	1,428	1,305	1,211	2,253	1,407	1,216

	Japan	Latvia	Lithuania	Mexico	Netherlands	New Zealand	Norway
Gender							
Female	681	550	679	928	817	627	697
Male	626	450	344	709	655	545	685
Age							
15-30	216	273	174	518	126	178	225
31-45	327	234	218	504	326	282	366
46-60	314	260	269	383	461	320	406
61-75	336	233	248	175	413	315	351
76+	114	0	114	57	146	77	34
Employment Status							
Employed	768	515	408	686	759	743	870
Unemployed	31	110	122	148	49	51	23
Student	74	92	64	164	32	41	115
Retired	245	52	34	387	105	74	17
Homemaker	38	33	54	158	110	17	128
Other	151	198	341	94	417	246	229
Highest Education							
No formal qualification	0	22	18	216	25	207	6
Lowest qualification	243	106	95	295	72	5	73
Intermediate secondary completed	0	82	211	338	623	103	282
Higher secondary completed	571	511	228	412	161	213	353
University degree uncompleted	242	70	246	73	116	393	178
University degree completed	251	209	225	303	475	251	490

	Japan	Latvia	Lithuania	Mexico	Netherlands	New Zealand	Norway
Marital Status							
Currently married	848	422	504	918	789	706	765
Currently not married	141	290	339	285	394	298	218
Never married	318	288	180	434	289	168	399
Self-rated Social Status							
10%	33	24	49	56	79	0	15
20%	73	69	125	183	84	0	32
30%	231	126	185	293	112	0	48
40%	254	173	202	338	122	0	104
50%	348	233	226	401	235	0	290
60%	206	163	128	192	245	0	393
70%	112	109	67	119	348	0	307
80%	42	65	28	47	191	0	157
90%	5	25	9	4	35	0	17
100%	3	13	4	4	21	0	19
not asked	0	0	0	0	0	1,172	0
Household Size							
1-person	103	199	274	92	376	134	250
2-person	322	291	353	262	595	491	529
3-person	287	230	174	329	181	220	203
4-person	335	191	150	392	206	195	228
5-person+	260	89	72	562	114	132	172

	Japan	Latvia	Lithuania	Mexico	Netherlands	New Zealand	Norway
Area of Residency							
City	122	446	351	719	292	220	346
Small City	805	220	443	659	534	727	491
Rural	380	334	229	259	646	225	545
Belong to a Religion							
Yes	458	722	942	1,545	853	782	1,116
No	849	278	81	92	619	390	266
Post-Materialistic Values							
Post-materialistic	80	50	36	195	204	100	137
Neither post-materialistic nor materialistic	991	660	765	812	924	754	900
Materialistic	236	290	222	630	344	318	345
Voting in the Last Election							
Yes	962	588	715	1,051	1,298	848	1,229
No	285	247	282	527	158	245	112
Not eligible to vote	60	165	26	59	16	79	41
Political Orientation							
Left	35	267	90	190	500	505	593
Centre	277	93	95	598	337	27	226
Right	293	75	80	254	569	601	418
No party affiliation	699	557	693	588	0	0	107
Other	3	8	65	7	66	39	38
not asked	0	0	0	0	0	0	0

	Japan	Latvia	Lithuania	Mexico	Netherlands	New Zealand	Norway
Mode of Data Collection							
Face-to-Face Interview (PAPI)	0	1,000	1,023	1,637	0	0	0
Face-to-Face Interview (CAPI)	0	0	0	0	0	0	0
Self-completed questionnaire (interviewer)	1,307	0	0	0	0	0	0
Self-completed questionnaire (mailed)	0	0	0	0	1,472	1,172	907
Self-completed questionnaire (CASI)	0	0	0	0	0	0	0
Self-completed questionnaire (web)	0	0	0	0	0	0	475
Phone Interview	0	0	0	0	0	0	0
Total	1,307	1,000	1,023	1,637	1,472	1,172	1,382

	Philippines	Portugal	Republic of Korea	Russian Federation	Slovakia	Slovenia	South Africa
Gender							
Female	600	595	832	1,060	698	590	1,844
Male	600	427	744	559	461	492	1,268
Age							
15-30	318	132	337	352	223	226	1,076
31-45	401	255	555	437	337	277	957
46-60	299	305	377	398	356	262	637
61-75	162	240	226	334	200	214	373
76+	20	90	81	98	43	103	69
Employment Status							
Employed	691	494	944	855	629	518	1,221
Unemployed	107	114	33	77	89	58	691
Student	39	34	105	69	82	111	291
Retired	265	51	210	94	50	35	191
Homemaker	50	65	252	60	26	31	293
Other	48	264	32	464	283	329	425
Highest Education							
No formal qualification	203	60	109	0	5	41	844
Lowest qualification	170	427	115	76	141	178	209
Intermediate secondary completed	177	168	176	397	370	204	745
Higher secondary completed	277	179	440	717	453	416	926
University degree uncompleted	228	9	357	68	26	109	183
University degree completed	145	179	379	361	164	134	205

	Philippines	Portugal	Republic of Korea	Russian Federation	Slovakia	Slovenia	South Africa
Marital Status							
Currently married	765	604	996	821	666	547	1,239
Currently not married	147	198	211	573	257	313	477
Never married	288	220	369	225	236	222	1,396
Self-rated Social Status							
10%	54	45	99	116	23	3	166
20%	55	62	82	160	72	17	301
30%	118	158	238	269	125	51	423
40%	176	200	265	264	198	102	520
50%	423	322	470	266	383	393	636
60%	208	119	230	374	196	246	446
70%	101	66	124	96	99	142	325
80%	49	34	55	62	50	87	199
90%	6	4	9	6	11	31	56
100%	10	12	4	6	2	10	40
not asked	0	0	0	0	0	0	0
Household Size							
1-person	23	168	287	390	141	118	329
2-person	116	366	373	483	318	256	557
3-person	198	226	375	417	268	228	609
4-person	243	191	413	206	278	283	541
5-person+	620	71	128	123	154	197	1,076

	Philippines	Portugal	Republic of Korea	Russian Federation	Slovakia	Slovenia	South Africa
Area of Residency							
City	372	130	445	746	179	146	1,961
Small City	257	526	914	463	466	281	285
Rural	571	366	217	410	514	655	866
Belong to a Religion							
Yes	1,197	924	894	1,396	933	798	2,686
No	3	98	682	223	226	284	426
Post-Materialistic Values							
Post-materialistic	72	112	155	24	66	75	339
Neither post-materialistic nor materialistic	613	643	814	543	626	623	1,755
Materialistic	515	267	607	1,052	467	384	1,018
Voting in the Last Election							
Yes	996	763	1,024	1,155	739	800	2,314
No	196	247	529	464	344	249	798
Not eligible to vote	8	12	23	0	76	33	0
Political Orientation							
Left	107	488	514	277	323	171	40
Centre	9	330	548	608	177	45	2,358
Right	79	92	514	75	71	216	156
No party affiliation	1,005	0	0	641	451	556	538
Other	0	112	0	18	137	94	20
not asked	0	0	0	0	0	0	0

	Philippines	Portugal	Republic of Korea	Russian Federation	Slovakia	Slovenia	South Africa
Mode of Data Collection							
Face-to-Face Interview (PAPI)	1,200	0	1,576	1,619	1,159	1,082	3,112
Face-to-Face Interview (CAPI)	0	1,022	0	0	0	0	0
Self-completed questionnaire (interviewer)	0	0	0	0	0	0	0
Self-completed questionnaire (mailed)	0	0	0	0	0	0	0
Self-completed questionnaire (CASI)	0	0	0	0	0	0	0
Self-completed questionnaire (web)	0	0	0	0	0	0	0
Phone Interview	0	0	0	0	0	0	0
Total	1,200	1,022	1,576	1,619	1,159	1,082	3,112

	Spain	Sweden	Switzerland	United Kingdom	United States
Gender					
Female	1,285	627	596	516	823
Male	1,275	554	616	412	607
Age					
15-30	449	204	223	122	293
31-45	767	284	312	272	382
46-60	651	339	348	238	382
61-75	460	307	235	218	263
76+	233	47	94	78	110
Employment Status					
Employed	1,339	722	742	504	802
Unemployed	307	62	31	54	123
Student	97	84	56	26	67
Retired	226	8	76	62	169
Homemaker	114	86	43	46	47
Other	477	219	264	236	222
Highest Education					
No formal qualification	246	10	7	239	24
Lowest qualification	536	213	194	56	63
Intermediate secondary completed	716	327	568	170	132
Higher secondary completed	546	176	96	134	412
University degree uncompleted	231	97	181	116	394
University degree completed	285	358	166	213	405

	Spain	Sweden	Switzerland	United Kingdom	United States
Marital Status					
Currently married	1,518	588	696	440	599
Currently not married	465	228	210	266	410
Never married	577	365	306	222	421
Self-rated Social Status					
10%	50	13	6	0	19
20%	95	16	8	0	16
30%	263	55	59	0	55
40%	415	83	120	0	122
50%	1,037	258	286	0	149
60%	444	350	253	0	516
70%	202	259	281	0	233
80%	45	100	159	0	185
90%	4	23	31	0	56
100%	5	24	9	0	79
not asked	0	0	0	928	0
Household Size					
1-person	226	217	218	254	437
2-person	760	499	456	331	508
3-person	648	164	198	149	216
4-person	664	190	226	129	154
5-person+	262	111	114	65	115

	Spain	Sweden	Switzerland	United Kingdom	United States
Area of Residency					
City	498	293	140	71	792
Small City	776	498	363	659	638
Rural	1,286	390	709	198	0
Belong to a Religion					
Yes	2,075	827	993	445	1,163
No	485	354	219	483	267
Post-Materialistic Values					
Post-materialistic	294	168	126	114	256
Neither post-materialistic nor materialistic	1,411	794	763	610	900
Materialistic	855	219	323	204	274
Voting in the Last Election					
Yes	1,944	978	656	0	1,003
No	561	121	289	0	427
Not eligible to vote	55	82	267	928	0
Political Orientation					
Left	513	579	231	311	505
Centre	49	191	68	137	565
Right	319	383	366	313	324
No party affiliation	1,657	0	529	139	0
Other	22	28	18	28	36
not asked	0	0	0	0	0

	Spain	Sweden	Switzerland	United Kingdom	United States
Mode of Data Collection					
Face-to-Face Interview (PAPI)	2,560	0	0	0	0
Face-to-Face Interview (CAPI)	0	0	1,212	0	1,283
Self-completed questionnaire (interviewer)	0	0	0	928	0
Self-completed questionnaire (mailed)	0	1,181	0	0	0
Self-completed questionnaire (CASI)	0	0	0	0	0
Self-completed questionnaire (web)	0	0	0	0	0
Phone Interview	0	0	0	0	147
Total	2,560	1,181	1,212	928	1,430

C.6 Descriptive Statistics of the Final Analysis Sample Dataset - Continuous Variables (By Countries)

	Arge: (N = 1	ntina ,,130)	Aust (N = 1		Aus (N = 1		Belg (N = 1		Bulg (N = 1	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Left-Right Ideology										
Private enterprise is the best way to solve economic problems	1.81	1.09	2.14	1.12	2.38	1.13	2.14	0.93	1.93	1.23
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	1.13	0.92	1.89	1.29	1.26	1.04	1.14	1.02	0.84	0.95
Social and Political Trusts										
Social Trust	2.20	2.05	4.54	2.22	4.34	1.97	4.20	2.27	2.34	2.01
Political Trust	2.35	1.51	3.32	1.86	2.75	1.89	3.25	1.59	2.16	1.72
Environmental Attitudes and Knowledge										
Environmental Risk Perception	21.13	3.92	17.40	4.74	19.82	4.12	16.77	4.36	20.34	4.32
Environmental Attitude	14.79	4.13	15.47	5.25	16.76	5.58	14.90	4.65	12.52	4.20
Attitudes towards Environment, Science and Economic Growths	6.99	2.32	9.14	2.63	8.00	3.02	8.59	2.52	7.09	2.46
Willingness to Make Personal Sacrifice for Environment	3.89	3.27	5.21	3.24	5.02	2.82	5.06	2.88	3.27	3.29
Environmental Knowledge	3.51	2.17	4.18	1.78	4.13	1.58	3.89	1.75	3.52	2.07

	Argentina (N = 1,130)		Australia (N = 1,946)		Austria (N = 1,019)		Belgium (N = 1,142)		Bulgaria (N = 1,003)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Environmental Justice and Global Cooperation										
For environmental problems, there should be international agreements that countries should be made to follow	0.87	0.70	1.13	0.93	0.68	0.78	0.96	0.75	0.55	0.61
Poorer countries should be expected to make less effort than richer countries to protect the environment	2.01	1.09	2.55	1.05	2.26	1.22	2.26	1.07	1.50	1.17

	Canada $(N = 985)$ Chile $(N = 1,436)$ Croatia $(N = 1,210)$ Czech Republic $(N = 1,428)$		Denmark (N = 1,305)							
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Left-Right Ideology										
Private enterprise is the best way to solve economic problems	2.08	1.12	2.07	0.97	2.14	1.15	2.17	1.16	2.29	1.23
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	1.71	1.30	1.41	0.94	1.11	0.98	1.43	1.19	1.55	1.34
Social and Political Trusts										
Social Trust	4.61	2.28	2.05	1.92	3.30	2.04	3.35	1.96	5.35	2.06
Political Trust	3.64	1.80	3.32	1.37	2.24	1.70	2.42	1.72	4.17	1.85
Environmental Attitudes and Knowledge										
Environmental Risk Perception	18.87	4.52	22.69	3.96	21.14	4.52	17.93	4.45	16.81	5.00
Environmental Attitude	17.18	4.83	14.53	4.01	14.68	4.66	13.89	5.01	16.27	6.02
Attitudes towards Environment, Science and Economic Growths	9.20	2.73	6.44	2.20	8.12	2.78	8.09	2.93	9.32	3.22
Willingness to Make Personal Sacrifice for Environment	5.58	3.06	5.40	2.95	3.39	2.92	3.57	2.89	6.27	2.77
Environmental Knowledge	4.28	1.80	3.23	2.14	4.07	1.94	3.49	1.83	4.10	1.75

		ada 985)	Ch (N = 1	_	Cro: (N = 1		Czech R (N = 1	epublic ,428)	Denn (N = 1	nark .,305)
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Environmental Justice and Global Cooperation										
For environmental problems, there should be international agreements that countries should be made to follow	0.96	0.80	1.06	0.86	1.14	0.90	0.70	0.80	0.73	0.99
Poorer countries should be expected to make less effort than richer countries to protect the environment	2.59	1.03	2.19	1.05	1.56	1.04	2.14	1.18	1.74	1.32

	Finl (N = 1		Fra (N = 2		Gern (N = 1		Isr (N = 1			oan 1,307)
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Left-Right Ideology										
Private enterprise is the best way to solve economic problems	2.28	1.03	2.26	1.23	2.39	1.10	2.03	1.09	1.37	1.01
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	1.13	1.14	1.00	1.21	1.43	1.21	0.89	0.94	1.37	1.10
Social and Political Trusts										
Social Trust	4.55	2.22	3.48	2.10	4.09	2.05	3.77	1.98	3.83	1.77
Political Trust	3.14	1.80	2.82	1.80	2.83	1.79	2.58	1.64	2.40	1.85
Environmental Attitudes and Knowledge										
Environmental Risk Perception	16.87	4.55	18.77	4.53	19.57	4.50	19.65	4.08	18.41	4.64
Environmental Attitude	16.39	5.03	14.74	5.74	15.58	5.31	14.47	4.44	14.06	4.59
Attitudes towards Environment, Science and Economic Growths	8.49	2.68	8.21	3.01	8.32	3.00	8.31	2.68	8.15	2.43
Willingness to Make Personal Sacrifice for Environment	5.10	2.80	4.74	3.04	5.54	2.83	5.21	2.78	5.03	2.75
Environmental Knowledge	4.52	1.72	4.04	2.01	4.04	1.80	4.05	2.16	3.40	1.79

	Finl (N = 1	-	Fra: (N = 2		Gern (N = 1		Isra (N = 1		Jap (N = 1	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Environmental Justice and Global Cooperation										
For environmental problems, there should be international agreements that countries should be made to follow	0.84	0.82	0.50	0.69	0.49	0.69	0.98	0.91	0.81	0.90
Poorer countries should be expected to make less effort than richer countries to protect the environment	1.89	1.15	2.12	1.30	2.05	1.27	1.45	1.10	2.15	1.16

	Latvia (N = 1,000)		Lithu (N = 1	-	Mex (N = 1		Netherlands 7) (N = 1,472)			
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Left-Right Ideology										
Private enterprise is the best way to solve economic problems	2.35	1.04	2.30	1.03	2.22	1.29	2.17	0.98	2.19	1.09
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	0.99	0.98	0.89	0.82	1.20	1.14	1.42	1.14	1.89	1.29
Social and Political Trusts										
Social Trust	3.38	1.97	3.32	1.75	3.02	1.98	5.18	2.29	4.85	2.25
Political Trust	1.82	1.51	2.06	1.44	2.27	1.82	4.10	1.66	4.00	1.73
Environmental Attitudes and Knowledge										
Environmental Risk Perception	18.15	4.85	20.17	4.05	20.97	4.85	16.46	4.50	17.70	4.90
Environmental Attitude	13.28	4.59	13.73	4.01	14.31	5.41	15.75	4.81	15.52	4.79
Attitudes towards Environment, Science and Economic Growths	8.19	2.87	7.89	2.49	6.04	2.77	8.68	2.71	8.54	2.69
Willingness to Make Personal Sacrifice for Environment	2.90	2.69	3.53	2.87	5.03	3.63	5.89	2.98	5.27	2.99
Environmental Knowledge	3.75	1.85	3.28	1.84	3.70	2.03	4.03	1.95	4.26	1.80

	Latvia (N = 1,000)		Lithuania (N = 1,023)		Mexico (N = 1,637)		Netherlands (N = 1,472)		New Zealand (N = 1,172)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Environmental Justice and Global Cooperation										
For environmental problems, there should be international agreements that countries should be made to follow	0.87	0.84	1.01	0.69	0.86	0.91	0.96	0.79	1.26	0.98
Poorer countries should be expected to make less effort than richer countries to protect the environment	1.38	1.12	1.83	1.04	1.97	1.28	2.11	1.13	2.55	1.05

	Norway (N = 1,382)		Philip (N = 1	-		Portugal (N = 1,022)		olic of rea ,576)	Russian Federation (N = 1,619)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Left-Right Ideology										
Private enterprise is the best way to solve economic problems	2.00	1.04	2.76	1.05	2.12	1.05	2.32	1.06	2.13	1.19
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	1.61	1.09	1.34	1.06	1.03	0.89	1.19	1.10	0.88	1.02
Social and Political Trusts										
Social Trust	5.68	1.97	3.49	2.03	2.85	2.04	3.86	1.78	3.41	1.86
Political Trust	4.39	1.71	3.50	1.68	2.15	1.49	2.76	1.69	3.09	1.74
Environmental Attitudes and Knowledge										
Environmental Risk Perception	16.24	4.21	20.75	4.45	20.49	4.06	18.79	4.23	21.74	4.54
Environmental Attitude	15.88	4.49	10.49	4.40	15.33	4.10	14.28	4.14	13.89	4.59
Attitudes towards Environment, Science and Economic Growths	9.79	2.54	6.43	2.85	7.35	2.42	7.68	2.49	7.60	2.75
Willingness to Make Personal Sacrifice for Environment	5.44	2.89	4.68	3.28	4.06	3.07	6.42	2.93	3.90	2.96
Environmental Knowledge	4.68	1.85	4.28	2.13	3.42	1.98	3.49	1.81	3.12	2.03

	Norway (N = 1,382)		Philippines (N = 1,200)		Portugal (N = 1,022)		Republic of Korea (N = 1,576)		Russian Federation (N = 1,619)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Environmental Justice and Global Cooperation										
For environmental problems, there should be international agreements that countries should be made to follow	0.89	0.67	0.98	0.89	0.86	0.65	0.72	0.77	0.81	0.87
Poorer countries should be expected to make less effort than richer countries to protect the environment	1.84	1.06	1.40	1.02	2.27	1.08	2.76	1.15	1.62	1.16

	Slovakia Slovenia South Africa Spain $(N = 1,159)$ $(N = 1,082)$ $(N = 3,112)$ $(N = 2,560)$			den 1,181)						
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Left-Right Ideology										
Private enterprise is the best way to solve economic problems	1.96	1.11	2.05	1.01	2.44	1.12	1.99	1.14	2.33	1.04
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	1.00	1.01	0.93	0.89	1.27	1.10	1.08	1.03	1.44	1.12
Social and Political Trusts										
Social Trust	2.94	1.90	3.00	1.96	3.29	2.07	3.44	1.88	5.19	2.05
Political Trust	2.24	1.72	2.18	1.52	3.21	1.63	2.81	1.75	4.07	1.68
Environmental Attitudes and Knowledge										
Environmental Risk Perception	19.68	4.36	19.78	3.82	19.61	5.41	20.22	3.92	17.19	4.53
Environmental Attitude	14.28	5.11	15.06	4.46	12.19	4.37	14.78	4.69	16.59	4.77
Attitudes towards Environment, Science and Economic Growths	7.80	2.86	7.42	2.72	6.83	2.98	7.73	2.63	9.06	2.75
Willingness to Make Personal Sacrifice for Environment	4.50	2.89	4.90	2.98	4.25	3.59	4.77	2.99	5.40	2.84
Environmental Knowledge	3.32	1.93	4.46	1.65	3.46	2.20	3.31	1.86	4.06	1.74

	Slovakia (N = 1,159)		Slov (N = 1	_	South Africa (N = 3,112)		Spain (N = 2,560)		Sweden (N = 1,181)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Environmental Justice and Global Cooperation										
For environmental problems, there should be international agreements that countries should be made to follow	0.93	0.95	0.85	0.64	1.02	0.82	0.58	0.68	0.83	0.80
Poorer countries should be expected to make less effort than richer countries to protect the environment	1.85	1.20	2.37	1.09	1.97	1.22	1.69	1.21	1.69	1.06

	Switzerland (N = 1,212)		United Kingdom (N = 9,28)		United (N = 1	
	Mean	SD	Mean	SD	Mean	SD
Left-Right Ideology						
Private enterprise is the best way to solve economic problems	2.41	0.90	2.16	1.01	2.23	1.14
It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes	1.66	1.12	1.60	1.12	2.34	1.24
Social and Political Trusts						
Social Trust	4.59	1.82	4.27	2.29	3.82	2.38
Political Trust	4.08	1.52	3.24	1.75	3.14	1.78
Environmental Attitudes and Knowledge						
Environmental Risk Perception	18.36	3.85	16.23	4.74	17.69	4.90
Environmental Attitude	16.80	4.24	14.07	5.06	15.17	4.87
Attitudes towards Environment, Science and Economic Growths	7.83	2.67	8.49	2.50	8.66	2.67
Willingness to Make Personal Sacrifice for Environment	6.74	2.59	4.67	3.11	5.48	3.28
Environmental Knowledge	4.17	1.64	3.93	1.82	3.43	1.92

	Switzerland (N = 1,212)		United Kingdom (N = 9,28)		United States (N = 1,430)	
	Mean	SD	Mean	SD	Mean	SD
Environmental Justice and Global Cooperation						
For environmental problems, there should be international agreements that countries should be made to follow	0.74	0.73	1.10	0.82	1.09	0.95
Poorer countries should be expected to make less effort than richer countries to protect the environment	2.18	1.17	2.34	1.02	2.57	1.01

C.7 Descriptive Statistics of the Country-level Variables

	Gini Coefficient	per capital GDP in PPP (in US Dollar)	Corruption Perceptions Index	Average Post- Materialistic Index	Environmental Performance Index	% of Population Satisfied with Air Quality	% of Population Satisfied with Water Quality	% of Population Satisfied with Government Actions
Argentina	48.8	8,662.99	2.9	1.38	49.20	75.0	73.8	33.9
Australia	35.2	54,868.92	8.7	1.10	82.20	93.1	93.4	63.8
Austria	29.1	43,723.32	7.9	1.13	78.90	88.0	97.1	63.9
Belgium	33.0	42,596.55	7.1	1.26	66.69	74.0	84.7	56.0
Bulgaria	29.2	5,954.72	3.6	1.43	64.12	69.3	60.8	19.4
Canada	32.6	45,887.74	8.9	1.01	73.03	84.5	91.3	61.7
Chile	52.0	11,587.09	7.2	1.16	69.17	69.5	84.5	42.1
Croatia	29.0	13,527.66	4.1	1.24	63.00	75.0	81.2	38.1
Czech Republic	25.8	18,721.63	4.6	1.31	81.93	69.0	89.2	56.6
Denmark	24.7	55,112.71	9.3	0.96	77.03	91.6	97.4	64.3
Finland	26.9	43,134.00	9.2	0.99	75.92	89.7	95.0	57.3
France	32.7	40,591.43	6.8	1.19	71.00	76.6	83.9	57.5
Germany	28.3	40,511.83	7.9	0.85	80.76	86.3	95.0	61.8
Israel	39.2	27,085.13	6.1	1.26	66.07	58.4	55.7	37.7
Japan	24.9	42,325.23	7.8	1.12	72.03	78.2	87.8	46.8
Republic of Korea	31.6	20,164.85	5.4	1.29	63.35	72.0	81.6	36.4
Latvia	36.3	10,377.78	4.3	1.24	63.49	75.1	65.3	38.9
Lithuania	35.8	10,765.34	5.0	1.18	60.88	70.2	69.7	29.9

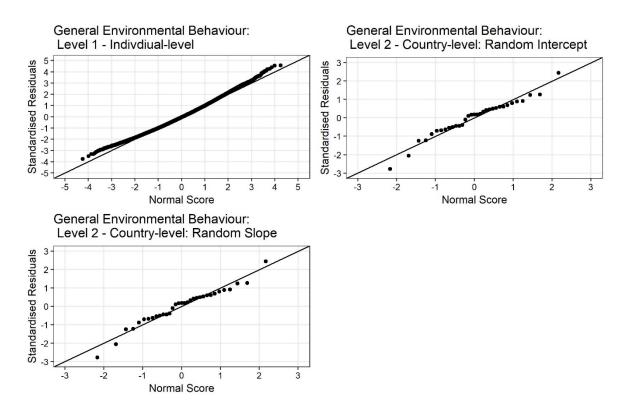
	Gini Coefficient	per capital GDP in PPP (in US Dollar)	Corruption Perceptions Index	Average Post- Materialistic Index	Environmental Performance Index	% of Population Satisfied with Air Quality	% of Population Satisfied with Water Quality	% of Population Satisfied with Government Actions
Mexico	51.6	9,243.03	3.1	1.27	54.66	78.0	67.7	46.8
Netherlands	30.9	46,418.33	8.8	1.10	76.92	81.5	94.2	66.1
New Zealand	36.2	31,588.78	9.3	1.19	76.31	93.0	89.0	74.8
Norway	25.8	84,543.44	8.6	1.15	77.97	89.3	95.3	51.5
Philippines	44.0	2,011.00	2.4	1.37	43.94	82.4	83.4	86.2
Portugal	38.5	21,030.61	6.0	1.15	75.50	85.7	90.0	37.2
Russian Federation	43.7	10,521.79	2.1	1.63	53.30	57.6	52.8	18.3
Slovakia	25.8	15,906.38	4.3	1.35	74.77	70.4	86.0	42.8
Slovenia	31.2	23,008.59	6.4	1.29	76.76	80.2	90.0	55.9
South Africa	57.8	7,100.81	4.5	1.22	53.00	85.7	53.4	55.7
Spain	34.7	29,875.09	6.1	1.22	79.60	82.0	83.6	46.0
Sweden	25.0	47,667.02	9.2	1.04	77.93	89.3	96.7	62.9
Switzerland	33.7	67,074.31	8.7	1.16	88.60	83.7	96.1	63.9
United Kingdom	36.0	36,298.39	7.6	1.10	77.09	88.8	94.8	66.8
United States	40.8	47,131.95	7.1	1.01	67.53	87.8	89.5	57.8

	Population Density	% of Population Lived in Urban Area	Education Index	% of Population Voiced Opinion to Public Officials	Human Development Index	Overall Life Satisfaction
Argentina	15.06	90.97	0.79	11	0.81	6.4
Australia	2.88	88.73	0.93	23	0.93	7.5
Austria	101.83	65.85	0.80	36	0.88	7.3
Belgium	360.96	97.64	0.82	23	0.88	6.9
Bulgaria	68.23	72.30	0.75	14	0.77	4.2
Canada	3.75	80.94	0.87	20	0.90	7.7
Chile	22.88	88.59	0.74	26	0.81	6.6
Croatia	77.13	57.54	0.76	19	0.81	5.6
Czech Republic	136.03	73.26	0.86	27	0.86	6.2
Denmark	130.83	86.80	0.89	37	0.91	7.8
Finland	17.66	83.56	0.81	19	0.88	7.4
France	114.99	78.35	0.81	23	0.88	6.8
Germany	230.76	74.29	0.88	35	0.91	6.7
Israel	342.90	91.82	0.85	18	0.88	7.4
Japan	349.25	90.52	0.81	22	0.88	6.1
Republic of Korea	504.89	81.94	0.86	22	0.89	6.1
Latvia	33.61	67.69	0.83	17	0.81	4.7
Lithuania	49.83	66.76	0.88	11	0.83	5.1
Mexico	61.02	77.83	0.63	22	0.75	6.8
Netherlands	493.23	87.06	0.87	30	0.91	7.5
New Zealand	16.59	86.17	0.92	23	0.90	7.2
Norway	13.39	79.10	0.91	31	0.94	7.6
Philippines	312.03	45.26	0.59	24	0.65	4.9

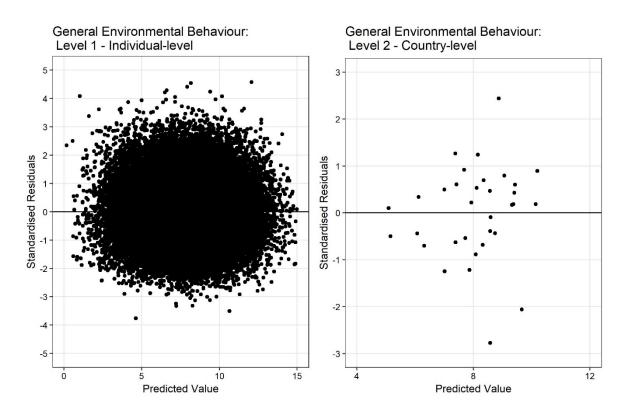
	Population Density	% of Population Lived in Urban Area	Education Index	% of Population Voiced Opinion to Public Officials	Human Development Index	Overall Life Satisfaction
Portugal	115.57	60.57	0.71	23	0.82	4.9
Russian Federation	8.74	73.69	0.79	13	0.78	5.4
Slovakia	112.44	54.69	0.80	14	0.83	6.1
Slovenia	101.91	50.04	0.86	36	0.88	6.1
South Africa	42.55	62.22	0.70	24	0.64	4.7
Spain	93.43	78.44	0.78	17	0.87	6.2
Sweden	22.86	85.06	0.84	29	0.90	7.5
Switzerland	198.16	73.66	0.86	36	0.92	7.5
United Kingdom	259.23	81.30	0.90	24	0.91	7.0
United States	33.88	80.77	0.89	32	0.91	7.2

C.8 General Environmental Behaviour: Model Validations and Diagnostics

C.8.1 Normal Plots for Country- and Individual-levels

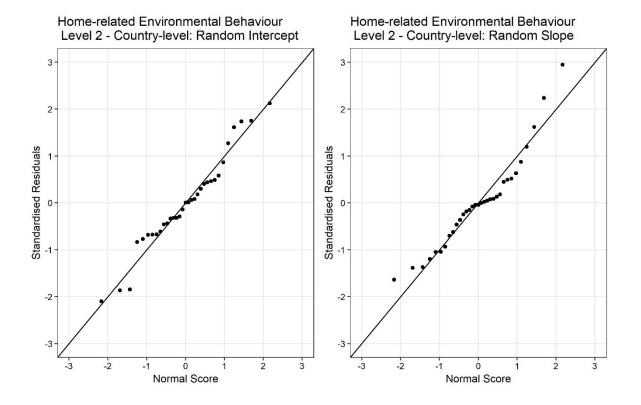


C.8.2 Plot of Standardised Residuals against Fitted Values

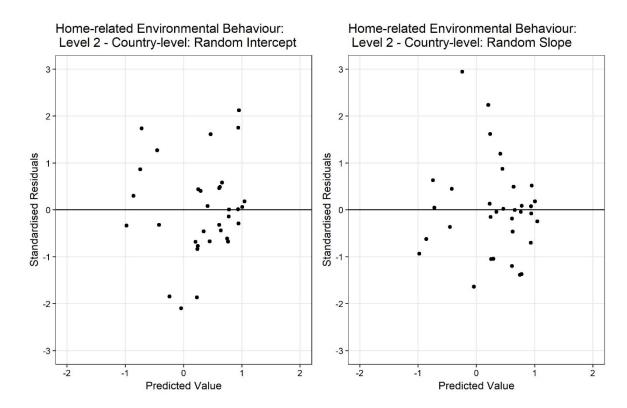


C.9 Home-related Environmental Behaviour: Model Validations and Diagnostics

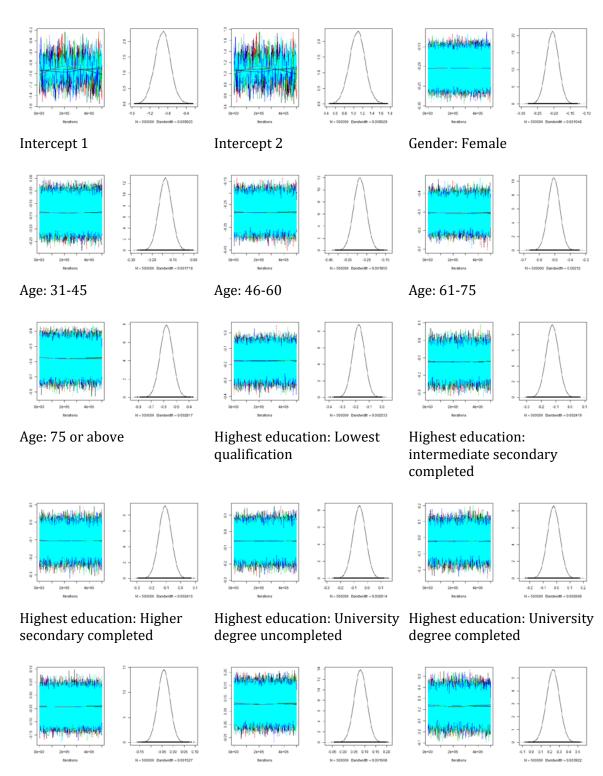
C.9.1 Normal Plots for Country- and Individual-levels



C.9.2 Plot of Standardised Residuals against Fitted Values

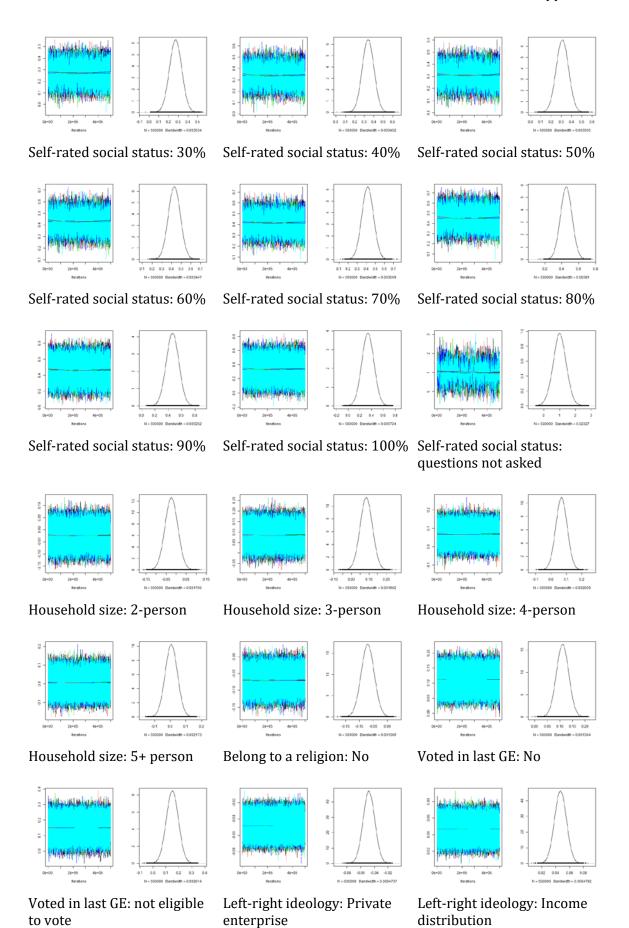


C.9.3 Trace Plots of the Estimates and the Kernel Density Plots of the Posterior Distributions



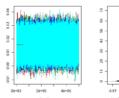
Marital status: Currently not married

Marital status: Never married $\,$ Self-rated social status: 20%

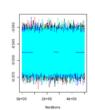


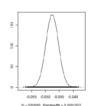
321

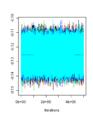
Appendix C

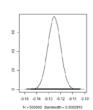






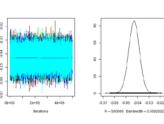




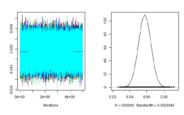


Social and political trust: Government are trustable

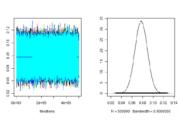
Environmental values: Risk perception



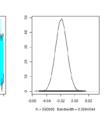
Environmental values: Knowledge



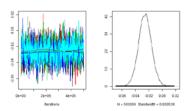
Environmental values: Personal sacrifice



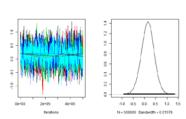
Environmental values: Attitudes



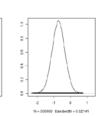
Environmental values: Modern technology



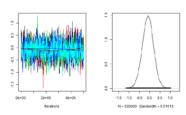
Environmental values: International agreement



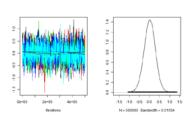
Environmental values: Poor countries are expected less



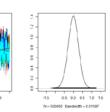
Country: % of water quality



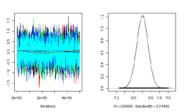
Mode of interview: F2F (CAPI)



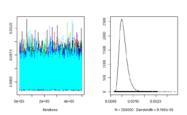
Mode of interview: SC (interviewer)



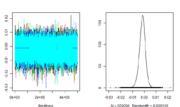
Mode of interview: SC (mailed)



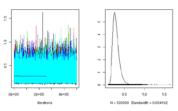
Mode of interview: SC (CASI)



Mode of interview: SC (web)

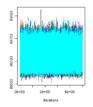


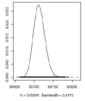
Mode of interview: Phone



Country (random intercept) Covariate between intercept and slope

Environmental concern (random slope)





DIC

C.9.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

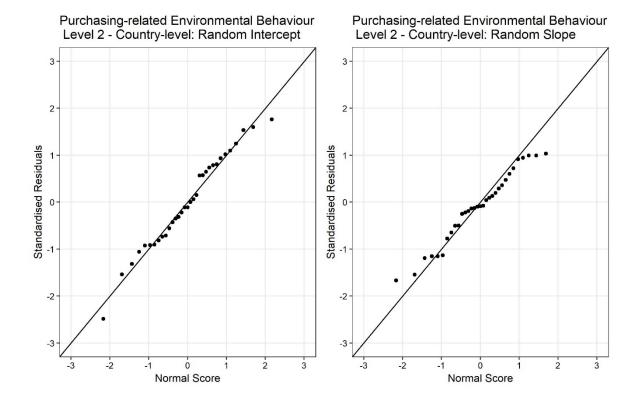
Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Fixed Effect		
Intercept 1	835	(1,981,899; 2,486,656)
Intercept 2	833	(1,917,056; 2,421,360)
Gender (Male)		
Female	201,908	(32,571; 30,348)
Age (15-30)		
31-45	54,387	(83,124; 87,660)
46-60	42,888	(111,343; 100,298)
61-75	40,313	(117,254; 84,456)
76 or above	56,676	(67,040; 85,284)
Highest education level (No formal qualification)		
Lowest formal qualification	33,557	(121,752; 118,675)
Intermediate secondary completed	27,089	(149,734; 157,963)
Higher secondary completed	25,602	(171,936; 164,940)
University degree uncompleted	28,692	(160,611; 133,196)
University degree completed	26,979	(138,446; 209,412)
Marital status (Currently married)		
Currently not married	95,889	(51,012; 40,270)
Never married	49,842	(85,804; 75,708)
Self-rated Social Status (10%)		
20%	16,733	(198,727; 200,695)
30%	13,128	(246,092; 246,205)
40%	12,297	(209,808; 313,548)
50%	11,609	(253,878; 288,956)
60%	12,007	(262,044; 315,645)
70%	12,475	(227,772; 306,264)
80%	13,799	(242,697; 288,956)
90%	30,216	(135,016; 107,544)
100%	38,487	(89,342; 101,544)
(question not asked)	2,791	(851,634; 744,370)
Household size (1-person household)		
2-person household	47,160	(86,400; 91,808)
3-person household	48,412	(98,692; 75,140)
4-person household	46,292	(80,316; 106,656)
5+ person household	51,132	(68,385; 74,592)
Belong to a religion (Yes)		·
No	84,714	(65,806; 66,287)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Voted in last GE (Yes)		
No	304,338	(23,945; 23,265)
Not eligible to vote	206,218	(32,312; 34,808)
Left-right ideology		
Private enterprise	443,783	(17,793; 17,127)
Income distribution	414,453	(18,375; 18,168)
Social and political trust		
Government is trustable	367,506	(20,184; 20,236)
Environmental values		
Environmental risk perception	321,149	(20,976; 21,420)
Environmental knowledge	371,707	(18,114; 20,104)
Willingness to make personal sacrifice	370,317	(20,388; 23,525)
Environmental attitudes	47,087	(110,880; 94,316)
Attitudes towards modern technology	352,828	(18,555; 18,171)
International agreement	406,180	(17,142; 17,820)
Poor countries are expected less	419,113	(15,724; 17,487)
Country-level		
% of water quality	1,333	(1,028,859; 1,396,460)
Mode of interview (F2F interview – PAPI)		
F2F interview (CAPI)	1,916	(1,569,780; 1,042,470)
SC (interviewer)	2,016	(1,853,280; 910,035)
SC (mailed)	1,106	(2,428,051; 1,213,534)
SC (CASI)	1,562	(2,365,120; 1,318,800)
SC (web)	1,414	(1,667,260; 1,047,016)
Phone interview	3,768	(839,520; 719,200)
Random Effect		
Country (random intercept)	501,504	(16,688; 19,415)
Covariate between intercept and slope	187,248	(15,104; 19,830)
Environmental concern (random slope)	48,041	(18,520; 46,068)
<u>DIC</u>	341,218	(16,184; 20,340)

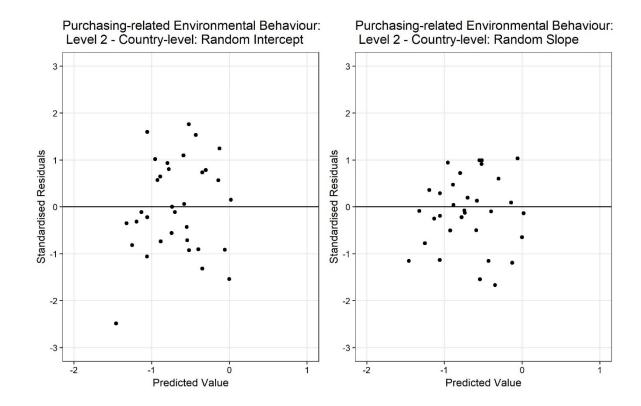
^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

C.10 Purchasing-related Environmental Behaviour: Model Validations and Diagnostics

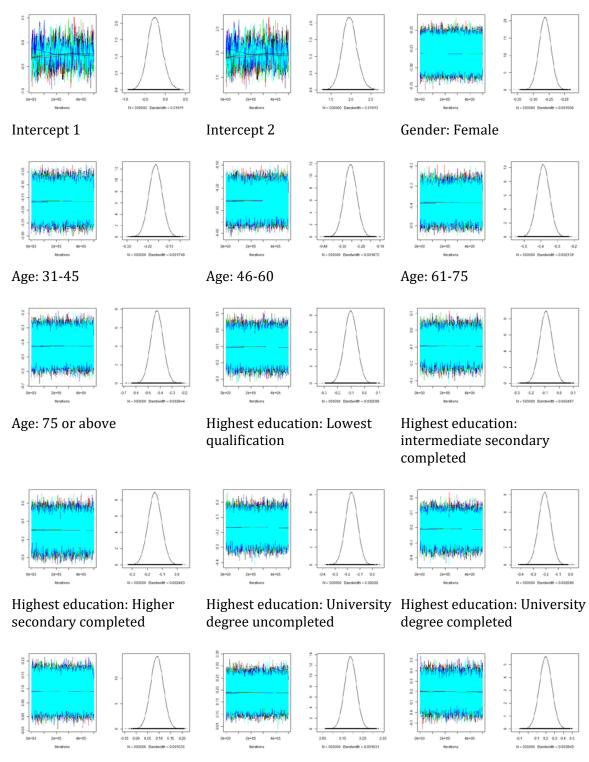
C.10.1 Normal Plots for Country- and Individual-levels



C.10.2 Plot of Standardised Residuals against Fitted Values

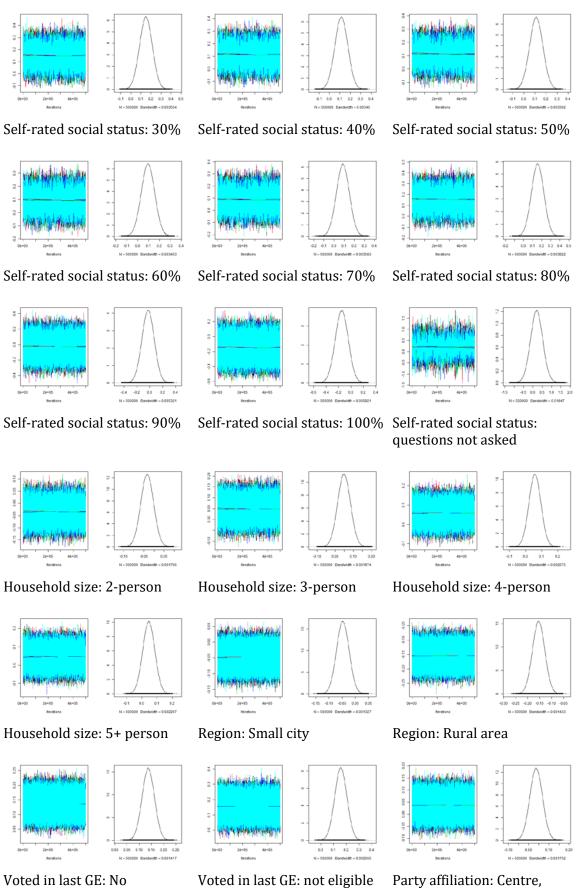


C.10.3 Trace Plots of the Estimates and the Kernel Density Plots of the Posterior Distributions



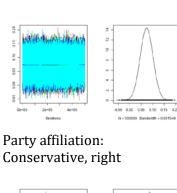
Marital status: Currently not married

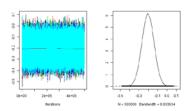
Marital status: Never married Self-rated social status: 20%

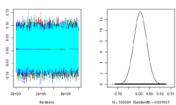


to vote liberal

Appendix C

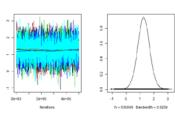


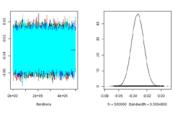


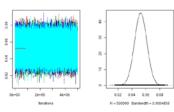


Party affiliation: No affiliation

Party affiliation: Other

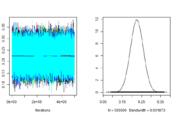




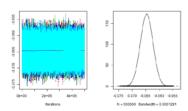


Party affiliation: questions not asked

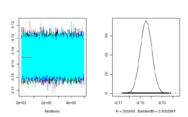
Left-right ideology: Private enterprise



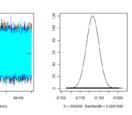
Left-right ideology: Income distribution



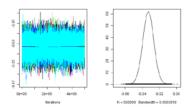
PM values: Neither postmaterialistic or materialistic



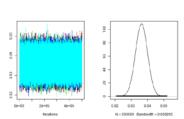
PM values: Materialistic



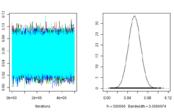
Environmental values: Risk perception



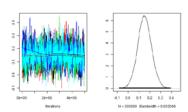
Environmental values: Knowledge



Environmental values: Personal sacrifice



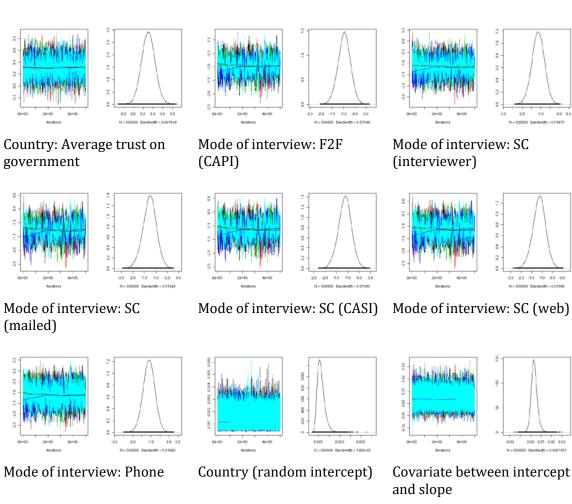
Environmental values: **Attitudes**



Environmental values: Modern technology

Environmental values: International agreement

Country: Corruption perception index



Environmental concern (random slope)

DIC

C.10.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

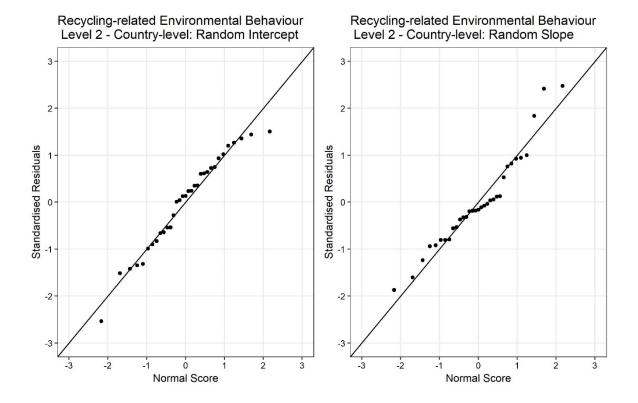
Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Fixed Effect		
Intercept 1	801	(2,852,288; 2,116,551)
Intercept 2	798	(1,996,145; 3,185,040)
Gender (Male)		
Female	193,510	(33,684; 32,830)
Age (15-30)		
31-45	55,618	(77,979; 92,547)
46-60	42,882	(104,302; 116,424)
61-75	39,355	(125,064; 117,598)
76 or above	56,037	(86,982; 84,284)
Highest education level (No formal qualification)		
Lowest formal qualification	30,650	(132,704; 121,100)
Intermediate secondary completed	25,677	(170,841; 147,987)
Higher secondary completed	24,180	(160,616; 154,280)
University degree uncompleted	26,508	(168,844; 142,128)
University degree completed	24,830	(172,143; 148,148)
Marital status (Currently married)		
Currently not married	94,993	(51,120; 43,100)
Never married	51,827	(87,738; 94,710)
Self-rated Social Status (10%)		
20%	17,494	(164,802; 191,634)
30%	13,522	(233,865; 269,664)
40%	12,665	(261,408; 268,793)
50%	11,974	(278,392; 337,550)
60%	12,251	(260,040; 277,920)
70%	12,833	(225,515; 284,544)
80%	14,399	(242,592; 216,174)
90%	31,199	(138,930; 77,760)
100%	40,780	(91,256; 107,825)
(question not asked)	4,668	(553,095; 712,530)
Household size (1-person household)		
2-person household	49,118	(87,448; 102,744)
3-person household	51,251	(87,419; 92,240)
4-person household	48,659	(86,670; 93,808)
5+ person household	55,326	(63,225; 81,198)
Region (Big city)		
Small city	130,565	(43,119; 35,469)
Rural area	126,138	(43,930; 38,136)

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Voted in last GE (Yes)		
No	280,467	(18,888; 21,256)
Not eligible to vote	207,700	(33,019; 32,557)
Party affiliation (Far left, left, centre left)		
Centre, liberal	144,420	(41,625; 44,940)
Conservative, right, far right	145,809	(43,820; 51,612)
Other	351,555	(19,792; 20,544)
No party affiliation	110,971	(42,543; 61,906)
(questions not asked)	5,563	(826,239; 608,856)
Left-right ideology		
Private enterprise	433,482	(17,433; 17,703)
Income distribution	389,084	(17,625; 20,032)
Post-materialistic values (post materialistic)		
Neither post-materialistic nor materialistic	49,219	(87,282; 82,704)
Materialistic	54,526	(87,246; 81,311)
Environmental values		
Environmental risk perception	316,119	(20,836; 21,232)
Environmental knowledge	374,435	(17,640; 17,310)
Willingness to make personal sacrifice	371,343	(20,328; 17,934)
Environmental attitudes	23,215	(177,475; 173,908)
Attitudes towards modern technology	358,439	(18,156; 18,432)
International agreement	407,802	(19,480; 17,826)
Country-level		
Corruption perception index	1,378	(1,449,828; 1,216,930
Average trust on government	3,040	(979,837; 1,082,562)
Mode of interview (F2F interview – PAPI)		
F2F interview (CAPI)	1,890	(1,709,004; 1,393,740
SC (interviewer)	2,651	(899,388; 978,536)
SC (mailed)	1,035	(1,837,836; 2,151,765
SC (CASI)	1,383	(2,279,678; 1,933,573
SC (web)	1,304	(1,673,434; 1,355,580
Phone interview	3,857	(635,819; 943,440)
Random Effect		
Country (random intercept)	604,870	(12,084; 15,288)
Covariate between intercept and slope	80,857	(27,881; 35,370)
Environmental concern (random slope)	37,486	(32,240; 96,950)
DIC	337,348	(16,692; 20,120)

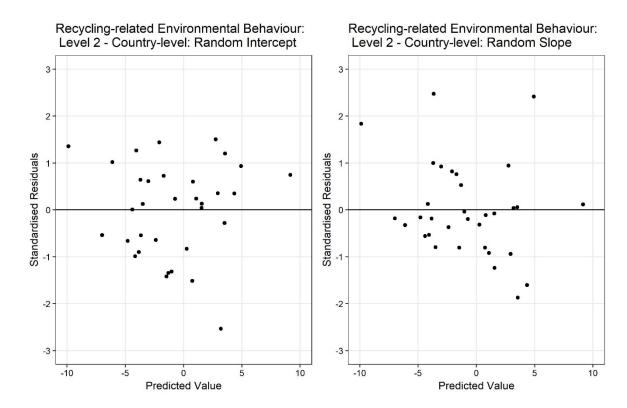
^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

C.11 Recycling-related Environmental Behaviour: Model Validations and Diagnostics

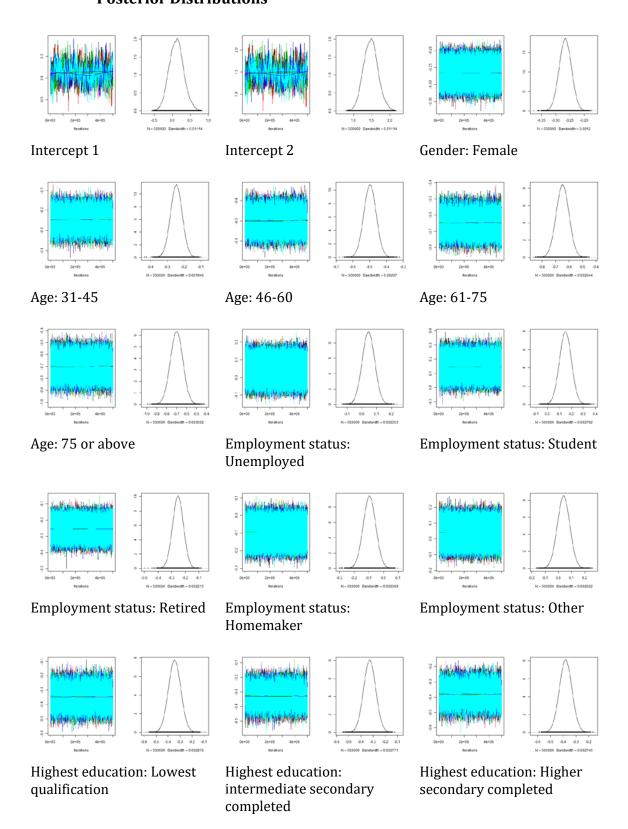
C.11.1 Normal Plots for Country- and Individual-levels

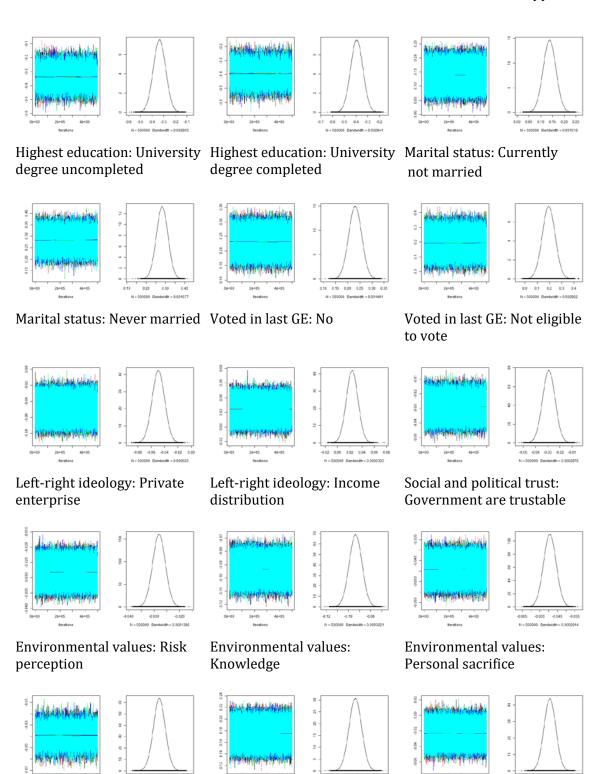


C.11.2 Plot of Standardised Residuals against Fitted Values



C.11.3 Trace Plots of the Estimates and the Kernel Density Plots of the Posterior Distributions



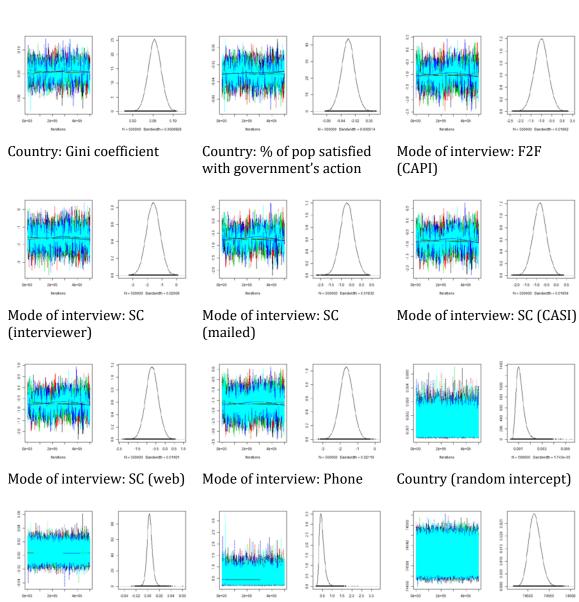


Environmental values: Attitudes

Environmental values: International agreement

Environmental values: Poor countries are expected less

Appendix C



Covariate between intercept and slope

Environmental concern (random slope)

DIC

C.11.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*		
Fixed Effect				
Intercept 1	616	(3,124,056; 1,652,490)		
Intercept 2	614	(3,205,245; 1,686,570)		
Gender (Male)				
Female	182,584	(29,532; 28,480)		
Age (15-30)				
31-45	49,930	(79,904; 80,546)		
46-60	43,851	(103,060; 86,887)		
61-75	44,463	(115,830; 97,000)		
76 or above	61,961	(80,180; 100,717)		
Employment status (Employed)				
Unemployed	369,571	(19,680; 17,142)		
Student	190,097	(25,280; 38,547)		
Retired	114,426	(52,128; 54,024)		
Homemaker	297,808	(26,502; 21,232)		
Other	337,453	(22,430; 18,027)		
Highest education level (No formal qualification)				
Lowest formal qualification	28,002	(149,885; 143,640)		
Intermediate secondary completed	22,282	(210,015; 158,937)		
Higher secondary completed	20,397	(174,150; 183,960)		
University degree uncompleted	23,324	(191,596; 166,208)		
University degree completed	22,056	(167,840; 185,999)		
Marital status (Currently married)				
Currently not married	287,762	(21,556; 21,352)		
Never married	94,900	(54,717; 50,652)		
Voted in last GE (Yes)				
No	303,736	(23,730; 20,908)		
Not eligible to vote	213,330	(31,927; 33,068)		
Left-right ideology				
Private enterprise	462,328	(15,164; 17,700)		
Income distribution	415,989	(15,778; 16,008)		
Social and political trust				
People are trustable	390,053	(18,351; 20,636)		

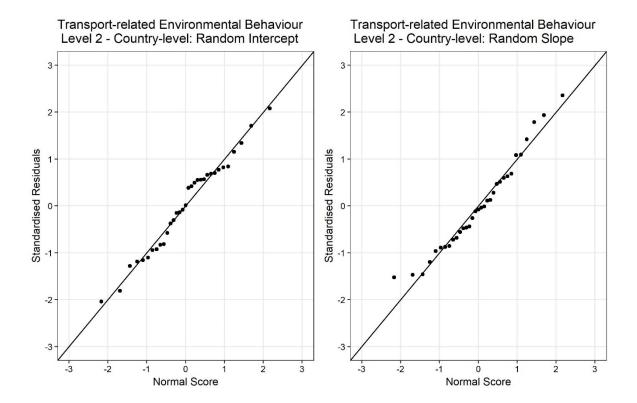
Appendix C

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*		
Environmental values				
Environmental risk perception	329,245	(21,696; 24,225)		
Environmental knowledge	376,433	(23,275; 23,095)		
Willingness to make personal sacrifice	386,615	(17,946; 19,928)		
Environmental attitudes	31,058	(144,552; 154,629)		
International agreement	407,595	(19,796; 19,568)		
Poor countries are expected less	434,735	(19,780; 15,356)		
Country-level				
Gini coefficient	1,357	(1,717,728; 1,238,079)		
% of pop satisfied with government's action	1,586	(1,299,531; 1,416,392)		
Mode of interview (F2F interview – PAPI)				
F2F interview (CAPI)	1,911	(1,171,890; 1,602,058)		
SC (interviewer)	2,045	(1,076,677; 1,233,360)		
SC (mailed)	1,057	(1,548,330; 1,879,316)		
SC (CASI)	1,459	(1,386,980; 1,756,215)		
SC (web)	1,250	(1,488,954; 2,229,600)		
Phone interview	3,118	(669,042; 786,352)		
Random Effect				
Country (random intercept)	596,364	(16,104; 15,540)		
Covariate between intercept and slope	85,120	(34,605; 32,872)		
Environmental concern (random slope)	38,081	(11,856; 599,088)		
DIC	388,696	(16,220; 15,816)		

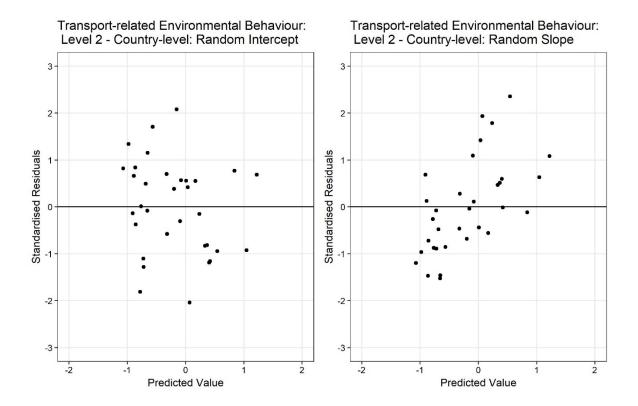
^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

C.12 Transport-related Environmental Behaviour: Model Validations and Diagnostics

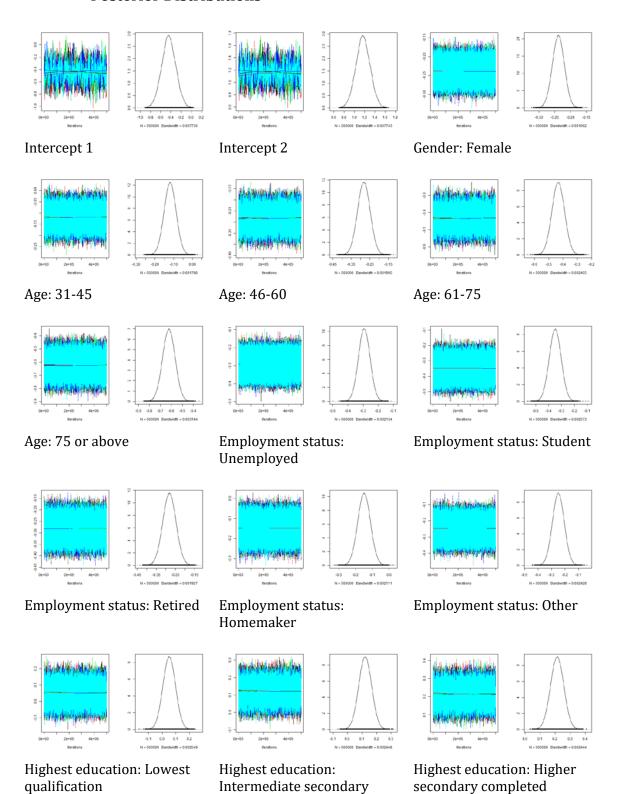
C.12.1 Normal Plots for Country- and Individual-levels



C.12.2 Plot of Standardised Residuals against Fitted Values

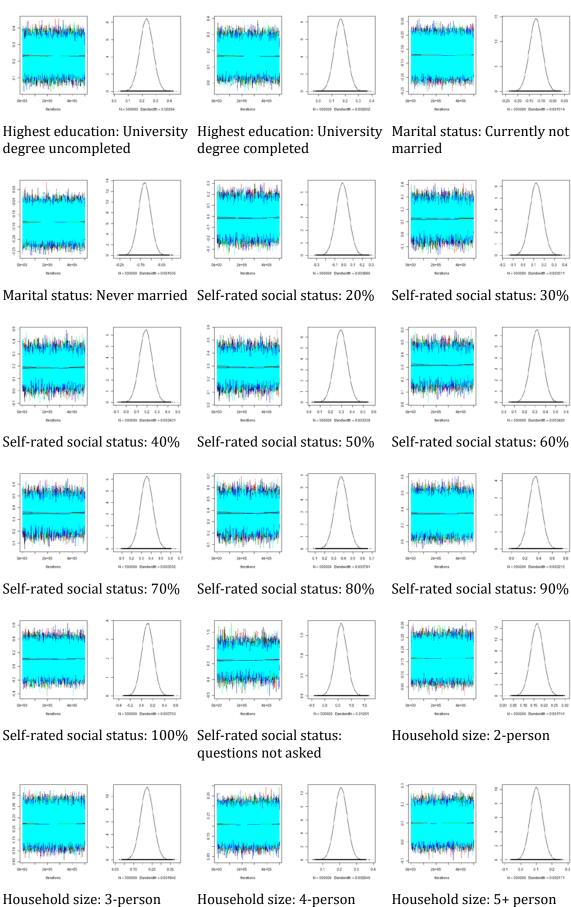


C.12.3 Trace Plots of the Estimates and the Kernel Density Plots of the Posterior Distributions

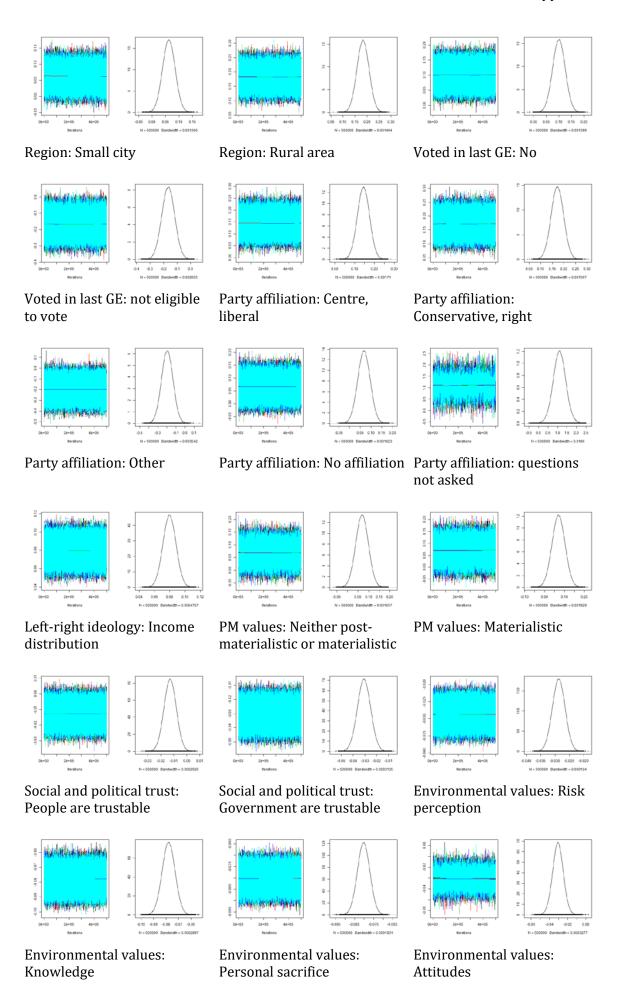


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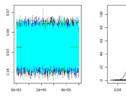
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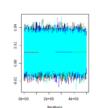
Household size: 3-person Household size: 4-person

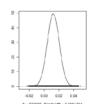


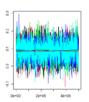
Appendix C

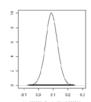






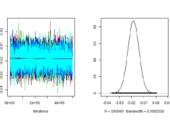




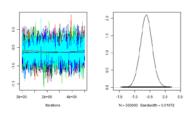


Environmental values: Modern technology

Environmental values: Poor countries are expected less

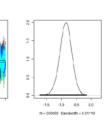


Country: Corruption perception index

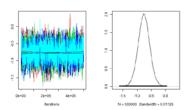


Country: % of air quality

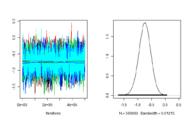
Country: % of pop satisfied with government's action



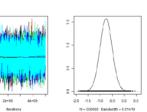
Mode of interview: F2F (CAPI)



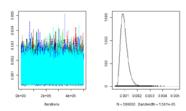
Mode of interview: SC (interviewer)



Mode of interview: SC (mailed)



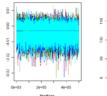
Mode of interview: SC (CASI)

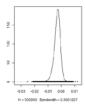


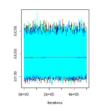
Mode of interview: SC (web)

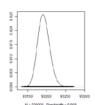
Mode of interview: Phone

Country (random intercept)









Covariate between intercept and slope

Environmental concern (random slope)

DIC

C.12.4 Effective Sample Sizes and Raftery-Lewis Diagnostics

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Fixed Effect		
Intercept 1	1,149	(1,932,528; 1,495,806)
Intercept 2	1,154	(2,051,316; 1,542,787)
Gender (Male)		
Female	183,349	(34,482; 37,112)
Age (15-30)		
31-45	48,785	(96,096; 65,745)
46-60	38,102	(105,777; 88,417)
61-75	38,022	(99,918; 113,424)
76 or above	52,389	(84,284; 74,880)
Employment status (Employed)		
Unemployed	342,404	(20,136; 17,838)
Student	209,553	(30,982; 24,870)
Retired	108,845	(56,823; 41,364)
Homemaker	310,944	(20,728; 20,356)
Other	331,381	(20,028; 19,576)
Highest education level (No formal qualification)		
Lowest formal qualification	32,571	(121,080; 139,048)
Intermediate secondary completed	25,735	(150,795; 152,670)
Higher secondary completed	24,584	(151,380; 185,185)
University degree uncompleted	26,862	(141,831; 139,854)
University degree completed	25,153	(157,113; 162,240)
Marital status (Currently married)		
Currently not married	94,166	(51,180; 53,652)
Never married	55,885	(72,576; 68,816)
Self-rated Social Status (10%)		
20%	16,957	(190,937; 216,480)
30%	13,262	(194,600; 279,150)
40%	12,097	(300,076; 266,208)
50%	11,443	(277,436; 299,712)
60%	11,820	(276,012; 283,600)
70%	12,474	(234,995; 286,656)
80%	13,882	(212,960; 240,924)
90%	29,716	(115,857; 143,847)
100%	39,359	(66,368; 65,926)
(question not asked)	9,528	(399,850; 341,520)

Appendix C

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*	
Household size (1-person household)			
2-person household	48,043	(105,094; 82,764)	
3-person household	49,598	(84,978; 74,664)	
4-person household	47,612	(97,671; 92,904)	
5+ person household	53,001	(82,602; 95,907)	
Region (Big city)			
Small city	125,854	(42,894; 39,520)	
Rural area	121,106	(42,696; 38,376)	
Voted in last GE (Yes)			
No	288,290	(24,080; 23,845)	
Not eligible to vote	210,373	(30,940; 25,625)	
Party affiliation (Far left, left, centre left)			
Centre, liberal	149,075	(37,816; 39,906)	
Conservative, right, far right	152,503	(40,059; 36,240)	
Other	368,521	(17,403; 15,584)	
No party affiliation	114,944	(46,240; 46,910)	
(questions not asked)	8,352	(420,336; 544,566)	
Left-right ideology			
Income distribution	400,320	(17,556; 17,433)	
Post-materialistic values (post materialistic)			
Neither post-materialistic nor materialistic	49,659	(107,100; 91,044)	
Materialistic	55,180	(86,887; 80,928)	
Social and political trusts			
People are trustable	355,669	(23,475; 20,936)	
Government are trustable	361,906	(20,244; 23,255)	
Environmental values			
Environmental risk perception	343,990	(18,072; 18,504)	
Environmental knowledge	363,898	(21,112; 20,572)	
Willingness to make personal sacrifice	354,454	(21,032; 20,912)	
Environmental attitudes	25,009	(172,492; 175,000)	
Attitudes towards modern technology	356,228	(20,936; 18,504)	
Poor countries are expected less	425,623	(17,520; 17,460)	
Country-level			
Corruption perception index	3,263	(999,600; 1,238,382	
% of pop satisfied with government's action	3,495	(667,940; 1,022,490	
% of air quality	5,984	(533,142; 531,753)	

Variable (Reference Category)	Effective Sample Size (ESS)	Raftery-Lewis Diagnostics (Nhat)*
Mode of interview (F2F interview – PAPI)		
F2F interview (CAPI)	3,662	(950,820; 992,979)
SC (interviewer)	5,749	(781,407; 484,512)
SC (mailed)	2,107	(1,032,264; 1,213,160)
SC (CASI)	3,048	(924,880; 1,600,340)
SC (web)	2,784	(833,690; 987,496)
Phone interview	9,335	(305,022; 360,300)
Random Effect		
Country (random intercept)	529,958	(12,225; 16,072)
Covariate between intercept and slope	19,129	(113,736; 178,815)
Environmental concern (random slope)	24,544	(53,846; 199,680)
DIC	292,676	(19,730; 20,765)

^{*} The Raftery-Lewis diagnostic (Nhat) are the estimated number of iterations required to estimate the default quantile (q) = 2.5% and 97.5% of the posterior distributions to a precision of tolerance (r) = 0.005 and probability (s) = 0.95.

C.13 Home-related Environmental Behaviour: Country Random Effect Variances, Credible Intervals, DICs and VPCs of the Multilevel Models

Model	σ_{u0}^2	(S.E.) §	[95% Cred Interval]	σ_{u01}	(S.E.) §	[95% Cred Interval]	σ_{u1}^2	(S.E.) §	[95% Cred Interval]
1.0									
1.1	0.4268	(0.1152)***	[0.2572, 0.7021]						
1.2	0.2942	(0.0859)***	[0.2320, 0.6503]						
1.3	0.2876	(0.0823)***	[0.0003, 0.0010]	-0.0016	(0.0027)	[-0.0072, 0.0036]	0.0006	(0.0002)**	[0.1686,0.4868]

 \overline{g} the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

	Variance	(S.E.) §	[95% Credible Interval]	VPC	DIC
None	0.4268	(0.1152)***	[0.2572, 0.7021]	0.115	94,698.2
Added Survey Design (6)	0.3907	(0.1086)***	[0.2379, 0.6868]	0.106	94,701.4
Added Individual's Sociodemographics (26)	0.4061	(0.1164)***	[0.2391, 0.6911]	0.110	93,924.1
Added Individual's Personal Values (6)	0.4083	(0.1172)***	[0.2106, 0.6080]	0.110	93,757.0
Added Individual's Environmental Values (7)	0.3595	(0.1028)***	[0.1703, 0.5029]	0.099	89,933.1
Added Country-level Variable (1)	0.2942	(0.0859)***	[0.2320, 0.6503]	0.082	89,932.9

 $[\]S$ the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

C.14 Purchasing-related Environmental Behaviour: Country Random Effect Variances, Credible Intervals, DICs and VPCs of the Multilevel Models

Model	σ_{u0}^2	(S.E.) §	[95% Cred Interval]	σ_{u01}	(S.E.) §	[95% Cred Interval]	σ_{u1}^2	(S.E.) §	[95% Cred Interval]
1.0									
1.1	0.3091	(0.0834)***	[0.1861, 0.5090]						
1.2	0.1844	(0.0565)***	[0.1040, 0.3220]						
1.3	0.1740	(0.0523)***	[0.0988, 0.3005]	0.0035	(0.0031)	[-0.0021, 0.0103]	0.0012	(0.0004)***	[0.0007, 0.0021]

 \S the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

	Variance	(S.E.) §	[95% Credible Interval]	VPC	DIC
None	0.3091	(0.0834)***	[0.1861, 0.5090]	0.086	94,435.3
Added Survey Design (6)	0.2903	(0.0833)***	[0.1696, 0.4913]	0.081	94,430.6
Added Individual's Sociodemographics (28)	0.3159	(0.0937)***	[0.1807, 0.5424]	0.088	93,363.0
Added Individual's Personal Values (11)	0.2557	(0.0763)***	[0.1454, 0.4402]	0.072	92822.3
Added Individual's Environmental Values (6)	0.2460	(0.0729)***	[0.1408, 0.4219]	0.070	88,142.9
Added Country-level Variables (2)	0.1844	(0.0565)***	[0.1040,0.3220]	0.053	88,142.4

 $[\]S$ the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

C.15 Recycling-related Environmental Behaviour: Country Random Effect Variances, Credible Intervals, DICs and VPCs of the Multilevel Models

Model	σ_{u0}^2	(S.E.) §	[95% Cred Interval]	σ_{u01}	(S.E.) §	[95% Cred Interval]	σ_{u1}^2	(S.E.) §	[95% Cred Interval]
1.0									
1.1	1.6819	(0.4477)***	[1.0200, 2.7517]						
1.2	0.4625	(0.1368)***	[0.2674, 0.7959]						
1.3	0.4715	(0.1324)***	[0.2783, 0.7918]	0.0035	(0.0048)	[-0.0056, 0.0138]	0.0012	(0.0003)***	[0.0006, 0.002]

 \S the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

	Variance	(S.E.) §	[95% Credible Interval]	VPC	DIC
None	1.6819	(0.4477)***	[1.0200, 2.7517]	0.338	78,844.7
Added Survey Design (6)	0.7562	(0.2079)***	[0.4501, 1.2554]	0.187	78,832.9
Added Individual's Sociodemographics (17)	0.7909	(0.2223)***	[0.4678, 1.3257]	0.194	76,988.3
Added Individual's Personal Values (5)	0.7927	(0.2243)***	[0.4675, 1.3346]	0.194	76,702.3
Added Individual's Environmental Values (6)	0.7688	(0.2166)***	[0.4538, 1.2898]	0.189	74,823.9
Added Country-level Variables (2)	0.4625	(0.1368)***	[0.2674, 0.7959]	0.123	74,823.6

 $[\]S$ the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

C.16 Transport-related Environmental Behaviour: Country Random Effect Variances, Credible Intervals, DICs and VPCs of the Multilevel Models

Model	σ_{u0}^2	(S.E.) §	[95% Cred Interval]	σ_{u01}	(S.E.) §	[95% Cred Interval]	σ_{u1}^2	(S.E.) §	[95% Cred Interval]
1.0									
1.1	0.1503	(0.0407)***	[0.0902, 0.2476]						
1.2	0.0707	(0.0239)**	[0.0374, 0.1293]						
1.3	0.0741	(0.0258)**	[0.0387, 0.1377]	-0.0031	(0.0024)	[-0.0083, 0.0011]	0.0010	(0.0003)***	[0.0006, 0.0017]

 \S the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

	Variance	(S.E.) §	[95% Credible Interval]	VPC	DIC
None	0.1503	(0.0407)***	[0.0902, 0.2476]	0.044	97,779.1
Added Survey Design (6)	0.1415	(0.0407)***	[0.0823, 0.2394]	0.041	97,780.7
Added Individual's Sociodemographics (33)	0.1736	(0.0512)***	[0.0996, 0.2969]	0.050	96444.3
Added Individual's Personal Values (12)	0.1691	(0.0517)***	[0.0956, 0.2945]	0.049	95811.7
Added Individual's Environmental Values (6)	0.1286	(0.0389)***	[0.0730, 0.2229]	0.038	93,505.2
Added Country-level Variables (3)	0.0707	(0.0239)***	[0.0374, 0.1293]	0.021	93,505.4

 $[\]S$ the asterisk * refers to the Wald test: *** indicates p-value ≤ 0.001 ; ** indicates p-value ≤ 0.01 ; * indicates p-value ≤ 0.05

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